



# The Impact of Weather on Local Government Spending

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**Abstract:**

While there is a new and rapidly growing literature on the effects of climatic factors on economic and social outcomes, little research has been conducted to understand the fiscal impact of weather, especially at the sub-state level. Using data from Massachusetts municipalities from 1990 through 2019, this paper estimates government spending as a function of temperature and precipitation while controlling for municipality and year fixed effects and municipality-specific time trends. The results show that weather has statistically significant and economically meaningful effects on local government spending. A 1 degree Fahrenheit increase in the average temperature results in a 3.2 percent increase in real per capita total general fund expenditures. Some government functions, such as public works and general government, are affected more by weather than others. The impact of weather may be persistent and heterogeneous across municipalities. There is some evidence that municipalities adapt to rising temperatures over time.

**JEL Classifications:** H72, Q51, Q54

**Keywords:** weather, climate, local government spending

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The author thanks Jeffrey Thompson, Kathy Bradbury, and participants at the Federal Reserve Bank of Boston Research Department's Brown Bag Seminar and the Federal Reserve System Climate Meeting for helpful comments. Eli Inkelas provided excellent research assistance.

This paper presents preliminary analysis and results intended to stimulate discussion and critical comment.

The views expressed herein are those of the author and do not indicate concurrence by the Federal Reserve Bank of Boston, the principals of the Board of Governors, or the Federal Reserve System.

This paper, which may be revised, is available on the website of the Federal Reserve Bank of Boston at <https://www.bostonfed.org/publications/research-department-working-paper.aspx>.

## I. Introduction

The ongoing debate on climate change has generated great interest in understanding how climatic factors affect economic and social activities. A new and rapidly growing literature examines the impact of weather conditions on various economic outcomes, including output, income, employment, productivity, inflation, housing construction and prices, energy demand, household finance, and banks' performance.<sup>1</sup> Other research studies the impact of weather on social outcomes, such as migration, mortality, hospitalization, crime, time allocation, and political stability. However, research on the fiscal impact of weather conditions is extremely limited. Furthermore, the few existing studies focus exclusively on how natural disasters affect government finances and household receipt of public assistance.<sup>2</sup>

To the best of my knowledge, this paper is the first to examine the impact of temperature and precipitation on local government spending. Using data from Massachusetts municipalities during a 30-year span from fiscal years (FY) 1990 through 2019, I estimate the relationship between government expenditures and a series of weather variables including average temperature, total precipitation, and measures of extreme temperature and precipitation. I use a panel data model with controls for municipality and FY fixed effects and municipality-specific time trends. By exploiting the exogeneity of weather variation within municipalities over time, this model allows the estimated effects of weather variables to be interpreted as causal.

## II. Model

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<sup>1</sup> See Dell, Jones, and Olken (2014) and Kolstad and Moore (2020) for a review of the climate-economy literature.

<sup>2</sup> See Noy and Nualsri (2011), Deryugina (2017), Deryugina, Kawano, and Levitt (2018), Miao, Hou, and Abrigo (2018), Jerch, Kahn, and Lin (2021), Tran and Wilson (2021), and Liao and Kousky (2022).

Weather can have a direct impact on government expenditures. Governments have to spend more on snow removal when their communities receive a larger amount of snowfall. They pay more to heat and cool public facilities when their communities experience more cold and hot days, respectively. Extreme temperatures and heavy rainfall and snowfall can damage streets and sidewalks and increase road maintenance costs. Weather can also have an indirect impact on government expenditures. Previous research shows that weather can affect a variety of economic and social activities and thereby impact the demand for and costs of providing public services. For example, Ranson (2014) finds that higher temperatures increase crime rates, which could raise public safety costs.

I use a cost-function framework to model the relationship between weather and government expenditures. This framework has been used extensively to explore the determinants of state and local government spending, especially public school spending. The cost function is typically written as

$$E = f(C, S, e), \quad (1)$$

where  $E$  is government spending,  $C$  is cost factors,  $S$  is service outcomes, and  $e$  is efficiency. This approach reveals how government spending responds to changes in cost factors, with outcomes and efficiency held constant. Cost factors are defined as community characteristics that affect government spending but are outside the direct control of government officials at any given time. In previous research, the set of cost factors is restricted to socioeconomic characteristics. For example, cost factors for public school spending often include the percentage of low-income students, the percentage of students with special needs, and the percentage of students who speak English as a second language. Building on that previous research, this paper uses weather as a cost factor.

I use a panel data model to estimate a reduced form of the cost function. The baseline specification is

$$\log E_{it} = \alpha W_{it} + \beta X_{it} + T_t + I_i + \gamma_i \times t + \theta + \varepsilon_{it}, \quad (2)$$

where  $\log E_{it}$  is the logarithm of real per capita government expenditures for municipality  $i$  in FY  $t$ ,<sup>3</sup>  $W_{it}$  is weather variables,  $X_{it}$  is time-varying control variables,  $T_t$  is FY fixed effects,  $I_i$  is municipality fixed effects,  $\gamma_i \times t$  is municipality-specific time trends,  $\theta$  is a constant term, and  $\varepsilon_{it}$  is an error term. I include two time-varying control variables: log real per capita property tax base and log real per capita state grants.<sup>4</sup> These are critical determinants of local revenue and spending. The per capita property tax base may correlate with weather because municipalities in coastal or mountainous regions can have distinct weather patterns, and their property values are often higher due to natural amenities. Per capita state grants may correlate with weather through their negative relationship with the per capita property tax base. State grants, especially those for public schools, are often distributed via equalization formulas, which allocate more aid dollars to places with lower per capita property values. The symbol  $\alpha$  is the coefficient of interest capturing the total (both direct and indirect) effects of weather. Estimated standard errors in this equation are clustered by municipality to allow for correlations within municipalities over time.

### III. Data

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<sup>3</sup> I also ran the same regression model on the log real per capita municipal total outstanding debt. The estimated coefficients on weather variables were not significant.

<sup>4</sup> Previous research shows that some socioeconomic and demographic characteristics of a community, such as income, age structure, educational attainment levels, and being part of a regional school district, could affect local spending (for example, Bradbury and Zhao 2009; Zhao 2022). Because these characteristics either do not change over time or move rather slowly, they can be controlled for by municipality and year fixed effects and municipality-specific time trends. In addition, data on many of these variables are not available for each municipality in every year, especially in the early part of the sample period.

I use Massachusetts data from FY1990 through FY2019 to estimate equation (2). The spending data were obtained from the Massachusetts Department of Revenue, which gathers detailed annual financial information on the state's 351 municipalities through the "Schedule A" form submitted by local government officials. This paper focuses on a city's or town's general fund, which is used to support daily operations and accounts for most financial activities governed by the normal municipal appropriation. It does not include spending funded by capital project,<sup>5</sup> trust, enterprise,<sup>6</sup> and other special funds.

General fund data include both total expenditures and major subcategory expenditures, such as public works, general government, education, police, fire, human services, and culture and recreation.<sup>7</sup> Because there are no powerful county governments in Massachusetts, municipalities are responsible for providing a wide range of public services.<sup>8</sup> However, not every municipality provides all types of services. Some towns with a small population do not have their own police and instead rely on state police. Small towns often also use volunteer firefighters and therefore report zero spending on fire safety. I exclude those towns from the regressions for police and fire

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<sup>5</sup> Data on municipal capital project funds in Massachusetts are available only for FY2003 onward. From FY2003 through FY2019, 217 out of 351 Massachusetts municipalities reported non-zero, non-missing values of total capital project fund expenditures each year. Using this data set, I tried estimating equation (2) with log real per capita capital project fund expenditures as the dependent variable. None of the estimated coefficients on weather variables was significant.

<sup>6</sup> Enterprise funds are used to fund municipal services for which a fee is charged, such as water and sewer services. Data on municipal enterprise funds in Massachusetts are available only for FY2004 onward. From FY2004 through FY2019, 206 out of 351 Massachusetts municipalities reported non-zero, non-missing values of total enterprise fund expenditures each year. Using this data set, I tried estimating equation (2) with log real per capita enterprise fund expenditures as the dependent variable. The estimated coefficients on weather variables were not significant.

<sup>7</sup> "General government" covers legislative, executive, accountant/auditor, collector, treasurer, law department, town/city counsel, public building/properties maintenance, assessors, operation support, license and registration, land uses, conservation commission, and other functions. "Public works" covers highways/streets snow and ice removal, highway/streets other, waste collection and disposal, sewerage collection and disposal, water distribution, parking garages, street lighting, and other functions. "Human services" covers health services, clinical services, special programs, veterans services, and other functions. "Culture and recreation" covers library, recreation, parks, historical commission, celebrations, and other functions.

<sup>8</sup> In Massachusetts, school districts are fiscally dependent on municipal governments. They do not have authority to raise tax revenues and instead rely on municipal appropriation and state grants.

spending.<sup>9</sup> I also exclude municipalities with missing values for the dependent variable in question in order to run a balanced panel regression.<sup>10</sup>

Panel (a) in Figure 1 shows that real per capita total expenditures exhibit a linear upward trend, which also exists for subcategory expenditures. The empirical model in equation (2) accounts for this time trend but also allows it to vary by municipality.

I obtain weather data from the Global Historical Climatology Network daily (GHCNd).<sup>11</sup> The data consist of daily weather records from ground stations across the world that undergo a common set of quality assurance reviews. While GHCNd includes numerous variables, five of them are designated as “core elements” and have the best data availability: minimum temperature, maximum temperature, precipitation, snowfall, and snow depth. I use the first four to construct weather variables for regression analysis. I compute daily average temperature as a simple average of minimum and maximum temperature. GHCNd has sparse information for other weather elements, such as wind speed and soil temperature, which are not used in this analysis.

Weather data need to be aggregated from the weather-station level to the municipality level to align with the spending data. First, I identify all weather stations within 50 miles of the centroid of each Massachusetts municipality. I follow Ranson (2014) and Wilson (2017) in using 50 miles

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<sup>9</sup> Municipalities that are dropped from the regression for police spending include Gosnold, Monroe, Mount Washington, and New Ashford. Municipalities that are dropped from the regression for fire spending include Adams, Barnstable, Buckland, Dalton, Dartmouth, Deerfield, Gosnold, Montague, Mount Washington, Oxford, Palmer, Plympton, South Hadley, Wareham, and Williamstown.

<sup>10</sup> Municipalities that are dropped from the regression for human services spending include Gosnold and New Ashford. Municipalities that are dropped from the regression for culture and recreation spending include Gosnold, Hawley, Mount Washington, and New Ashford. Due to missing data, Gosnold, which often has fewer than 100 residents and is the smallest community in the state, is also dropped from the regressions for total expenditures public works, general government, and education spending.

<sup>11</sup> To the best of my knowledge, there are no data on natural disasters at the municipality level. Existing data sets of natural disasters—FEMA Disaster Declarations Summaries, NOAA Storm Events Database, and SHELDDUS—are available only at the county and state levels and thus not suitable for analysis in this paper.

as a cutoff to identify relevant stations.<sup>12</sup> During the FY1990–FY2019 period, there were more than 1,100 unique stations within 50 miles of the centroid of at least one Massachusetts municipality. Next, I use the inverse of the distance between the centroid and each relevant weather station to weigh that station’s data and use the weighted average for each weather variable as the daily value for that municipality.

I further aggregate the daily weather data to the fiscal-year level to align with the annual spending for each municipality. I calculate the annual mean of daily average temperature and the yearly total of precipitation and snowfall. To test the effects of extreme weather events, I also calculate the percentage of days in each fiscal year with a maximum temperature of 90 degrees Fahrenheit or hotter, the percentage of days with a maximum temperature of 32 degrees Fahrenheit or colder, the percentage of days with at least 1 inch of precipitation, and the percentage of days with at least 1 inch of snowfall.<sup>13</sup> Including these measures of extreme temperature and precipitation helps to account for a possible nonlinear relationship between weather and municipal spending.<sup>14</sup>

Panels (b) through (h) in Figure 1 show that there was considerable variation over time for these weather variables. They also suggest that Massachusetts became hotter and wetter over the 30-year period. The annual average temperature for Massachusetts municipalities increased about

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<sup>12</sup> I tried reducing the cutoff to 40 miles, but doing so leaves no relevant weather stations for a few municipalities for part of the sample period.

<sup>13</sup> I tried including the standard deviation of the daily average temperature for each municipality in each year as a measure of annual temperature volatility. It is positive and significant at the 5 percent level in the regression for total expenditures when the full sample is used. However, it becomes insignificant and much smaller after I drop the 11 smallest municipalities (a robustness check conducted in Table 3). Given that the results on this variable are sensitive to the sample selection, I exclude it from the main regressions. Including this variable does not affect the results on other weather variables.

<sup>14</sup> I tried adding the quadratic terms of all seven weather variables to the model. A Wald test found that these quadratic terms are not jointly significantly different from zero and therefore do not need to be included in the regression for total expenditures.

0.04 degree Fahrenheit per year, on average (Panel b). This is similar to Mohaddes et al.'s (2022) estimate that the average yearly rise in temperature for Massachusetts over the period of 1963 through 2016 was 0.03 degree Celsius or 0.05 degree Fahrenheit. Runkle et al. (2022) also observe that the temperature for Massachusetts has been trending upward since 1960.

#### IV. Results

Table 1 shows the baseline regression results.<sup>15</sup> Column 1 indicates that total expenditures are affected by average temperature and the frequency of very cold days and heavy snowfall. A 1 degree Fahrenheit rise in the average temperature, on average, results in a 3.2 percent increase in real per capita total expenditures. This corresponds to an increase of \$100 per capita (in 2019 dollars) if real per capita total expenditures are set to the statewide average during the FY1990–FY2019 period, which was \$3,108 per capita (in 2019 dollars). A 1 percentage point increase in the percentage of days with a maximum temperature of 32 degrees Fahrenheit or colder or in the percentage of days with at least 1 inch of snowfall, on average, leads to a 0.4 percent increase in real per capita total expenditures, or an increase of \$12 per capita if evaluated at the 30-year statewide average real per capita total expenditures.

Other columns in Table 1 explore heterogeneity of weather effects by government function, which helps to shed light on the channels through which weather affects total expenditures. Public works, general government, and human services appear to be affected more than other government functions, as they have more significant results. Average temperature has a positive effect on spending on public works, general government, and fire, but a negative effect on spending on

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<sup>15</sup> The two time-varying control variables—log real per capita property tax base and log real per capita state grants—are positive and significant in the regressions. This is consistent with the hypothesis that revenue capacity contributes to local spending. I omit their estimates from Table 1 to simplify the presentation.



human services.<sup>16</sup> The percentage of days with a maximum temperature of 32 degrees Fahrenheit or colder positively affects spending on general government, education, and culture and recreation, while negatively affecting spending on human services. The effect of the percentage of days with at least 1 inch of snowfall on total expenditures is mostly channeled through its impact on general government spending. In addition, the coefficient on total snowfall in the regression for public works is positive and highly significant. This is consistent with the intuition that more snowfall results in higher costs for snow removal and road maintenance.

Table 2 tests the robustness of the results to potential measurement error in weather variables. I implicitly use weather at the centroid of each municipality to represent weather for the whole municipality. This is a reasonable assumption, especially if a municipality has a small and circular-shaped area. However, if the municipality is large and far from circular in shape, weather at the centroid could be a poor representation of weather for the whole municipality. In Massachusetts, most municipalities are indeed small. Almost two-thirds of the municipalities, or 230, have an area smaller than 25 square miles.<sup>17</sup> Another 31 percent, or 110 municipalities, are medium sized, with an area of 25 to 50 square miles. Only 11 municipalities (including Boston) are larger than 50 square miles. To measure a municipality's circularity, I calculate the ratio of the municipality's area to the area of its minimum bounding circle. The smaller this ratio, the further the municipality's shape departs from a circle. Among Massachusetts municipalities, the circularity measure ranges from 0.07 to 0.80, with a median of 0.49. In Table 2, I drop the 11 largest municipalities, each of which is larger than 50 square miles, regardless of their circularity

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<sup>16</sup> In the regression for human services, the estimated coefficients on average temperature and the percentage of days with a maximum temperature of 32 degrees Fahrenheit or colder are negative. This is likely because municipal governments choose to cut back on human services in order to spend more on other functions in response to temperature changes while satisfying the balanced-budget requirement.

<sup>17</sup> The area of these municipalities is smaller than the 5-mile-by-5-mile square that Ranson (2014) and Wilson (2017) use to divide the continental U.S. area.

measures. I also exclude 14 medium-sized municipalities with a shape that least resembles a circle. They each have an area of 25 to 50 square miles and a circularity measure of less than 0.4. These 25 municipalities are cases where measurement error in weather variables could be the largest. This sample restriction turns out to have little impact on the results. The coefficients that are significant in Table 1 remain significant with similar magnitudes in Table 2. The one exception is the percentage of days with a maximum temperature of 32 degrees Fahrenheit or colder. In the regression for education spending, it changes from being significant at the 10 percent level to being insignificant, although the point estimates are similar.

Table 3 tests whether the results are sensitive to data noise in spending variables. Municipalities with a small population often do not have full-time fiscal officers. These municipalities' financial accounts are less likely to be professionally managed and carefully recorded. Therefore, the financial data they submit to the state through the "Schedule A" form may contain large errors. To reduce the influence of this potential data issue, I drop 11 municipalities that had a population smaller than 500 at any time during the FY1990–FY2019 period. The coefficients that are significant in Table 1 remain significant in Table 3, except that total precipitation becomes insignificant in the regression for police spending.

In Table 4, I re-estimate the baseline model using weighted regressions to check whether the results remain significant. In Panel (a), municipality area is used as the weight to reduce the influence of small municipalities and increase the influence of large municipalities such as Boston. I do not use population as the weight because the population distribution in Massachusetts is extremely skewed. The 10 largest cities are home to one-quarter of the state's population, and Boston itself hosts nearly 10 percent of the Massachusetts population. The population-weighted sample essentially reflects only a small number of the most populous cities. In comparison, the

distribution of municipality area is less skewed. While Boston is one of the largest municipalities by area (ranking 11th), it accounts for only 0.6 percent of the state's total area. The significant results in the unweighted regressions remain significant in these weighted regressions, with one exception: In the regression for fire spending, average temperature turns from being significant at the 10 percent level to being insignificant, even though the point estimate does not change much.

In Panel (b), the weight is the inverse of the coefficient of variation of station count. Due to entry and exit of weather stations, the number of relevant stations for each municipality varies from year to year. This could introduce measurement error in weather data, since stations in different locations within a municipality's 50-mile radius may be subject to slightly different weather conditions. The greater the turnover in weather stations, the larger the potential measurement error. I calculate the coefficient of variation of annual station count for each municipality during the FY1990–FY2019 period as a measure of station turnover. I then use its inverse as a weight so that municipalities with a greater change in station count receive a smaller weight in the regression. The results from the weighted regressions in Panel (b) are close to those from the unweighted regressions in terms of both statistical significance and magnitude. Nevertheless, average temperature becomes insignificant in the regression for fire spending, while it is significant at the 10 percent level in the unweighted regression. Also, the percentage of days with a maximum temperature of 32 degrees Fahrenheit or colder becomes insignificant in the regressions for general government and education spending despite being significant at the 10 percent level in the unweighted regressions.

Weather may affect not only current government spending but also future government spending. For example, rainfall and snowfall could cause damage to roads and public facilities that is repaired in subsequent years. To test this hypothesis, I add lagged versions of weather variables

to the baseline model. A Wald test supports including both one-year and two-year lags of weather variables for total expenditures and public works spending, only the one-year lag of weather variables for education and police spending, and no lagged variables for other spending categories. Table 5 shows that the contemporaneous terms of weather variables that are significant in the baseline model remain significant after the inclusion of lagged variables. Some of these lagged weather variables are significant and mostly positive, which suggests that weather effects could be persistent at least in the short term. In some cases, the one-year lagged variables are significant, while the contemporaneous variables are not.<sup>18</sup> These results suggest that it may take time for municipal governments to adjust their budgets in response to weather changes.

Weather effects may be heterogeneous because of geographic and demographic differences between municipalities. Runkle et al. (2022) point out that the Massachusetts “coastline is highly vulnerable to damage from powerful nor’easters and tropical storms and hurricanes” (P. 3). To test whether the effects of weather differ by coastal adjacency, I add interaction terms between weather variables and a dummy variable for being a coastal community (Table 6). Massachusetts has 78 municipalities that are considered coastal communities. The interactions between the coastal dummy and temperature variables are not significant in the regression for total expenditures. The interactions between the coastal dummy and the percentage of days with at least 1 inch of precipitation or snowfall are positive and significant not only for total expenditures but also for multiple subcategories. This suggests that heavy rainfall and snowfall cause larger damages to coastal municipalities, resulting in higher expenditures. These results may also reflect other adverse weather conditions facing coastal municipalities that correlate with heavy rainfall and

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<sup>18</sup> See the contemporaneous and one-year lagged terms of average temperature in the regressions for education and police spending and the contemporaneous and one-year lagged terms of the percentage of days with a maximum temperature of 32 degrees Fahrenheit or colder in the regressions for public works and police spending.

snowfall. Nor'easters, tropical storms, and hurricanes can bring powerful wind, coastal flooding, shoreline erosion, and saltwater intrusion to coastal communities. Because I do not observe and control for these other weather elements, their effects on coastal communities could be partly captured by the interactions between the coastal dummy and the percentage of days with at least 1 inch of precipitation or snowfall.

On the other hand, the interaction term between the coastal dummy and total precipitation is negative and significant for both total expenditures and almost all spending subcategories, which suggests that an increase in total annual precipitation has a smaller impact on coastal municipalities than on inland communities. This may seem counterintuitive, but a possible explanation is that coastal municipalities are more likely to take steps to prepare for major storms and hurricanes, such as adopting new technologies and employing stricter zoning rules, which could help them reduce the fiscal impact of routine precipitation.

Densely populated urban areas are often noted as being more vulnerable to climate change compared with sparsely populated rural areas (Runkle et al. 2022). Heat waves, storms, and flooding could cause greater damage to urban areas with a high density of population and valuable properties. However, the economies of urban areas may be less dependent on weather compared with the economies of rural areas where agriculture plays an important role. Urban areas also enjoy an advantage in economies of scale, which could help them address adverse weather conditions better than rural areas. Therefore, the prediction on the difference in weather effects on urban versus rural areas is ambiguous.

To test for heterogeneity in weather effects on urban versus rural areas, I interact weather variables with a density dummy in Table 7. This density dummy is equal to 1 if the FY1990–FY2019 average population density for a municipality was equal to or greater than 3,000 people

per square mile. There are 35 such municipalities in Massachusetts. The results for these interaction terms are mixed. On the one hand, the interactions between the density dummy and average temperature, the percentage of days with a maximum temperature of 32 degrees Fahrenheit or colder, and total precipitation are negative and significant for both total expenditures and multiple spending subcategories. This suggests that government spending in high-density urban areas is less affected by a change in average temperature, the frequency of very cold days, and total precipitation, possibly thanks to their economies of scale and economic structures that are less dependent on weather. On the other hand, the interaction term between the density dummy and the percentage of days with at least 1 inch of precipitation is positive and significant in the regressions for total expenditures and fire spending. This suggests that extreme precipitation events could cause greater harm to high-density areas and result in more government spending.

Municipalities can mitigate the effects of weather by adapting over time. They can upgrade public facilities to be more energy efficient, use new technologies and materials to make roads more durable and heat-resistant, and adjust their zoning policies to make buildings more resilient to climate change. However, it takes time for these adaptation strategies to be adopted and produce results.

Table 8 examines whether municipal governments have adapted to their weather in the medium run.<sup>19</sup> I create a dummy variable to indicate the second half of the sample period (that is, FY2005 through FY2019) and then interact it with weather variables. By doing so, I compare

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<sup>19</sup> I tried exploring the difference between municipalities in their long-term weather patterns to test for municipal adaption to their local climate. For example, an increase in total snowfall may have a smaller effect for a municipality that tends to receive more snowfall and has adapted to its snowy climate. To test this hypothesis, I added interactions between each weather variable and the 30-year average of this variable for each municipality. These interaction terms were rarely significant and had mixed signs across spending categories. I consider this test to have a low power because the cross-sectional variation in long-term weather patterns is small in this context. All municipalities are from a single state that is relatively small, and therefore they face a similar climate.

average weather effects in the latter 15 years with average weather effects in the earlier 15 years. The interactions with average temperature and the frequency of very cold days are negative and significant for total expenditures and multiple spending subcategories. These results support the notion that municipal governments have adapted and become less sensitive to temperature over the years. However, I do not find strong evidence for adaptation to precipitation in the medium run. The interaction between total precipitation and the dummy for the FY2005–FY2019 period is positive and significant for total expenditures and fire spending, but it is negative and significant for general government spending.

## V. Conclusion

This paper fills a gap in the climate-economy literature by examining how weather affects local government spending. It uses a panel data model to analyze data from Massachusetts municipalities during a 30-year span from FY1990 through FY2019. The analysis shows that temperature and precipitation have statistically significant and economically meaningful effects on municipal expenditures. For example, a 1 degree Fahrenheit increase in the average temperature, on average, results in a 3.2 percent increase in real per capita total general fund expenditures. Further analysis suggests that government spending may be affected by not only contemporaneous weather conditions but also weather conditions in the preceding two years.

Weather effects appear to be heterogeneous across government functions. Spending on public works, general government, and human services are affected more than other spending categories. Weather also affects different types of municipalities differently. Coastal communities and densely populated cities experience a greater impact of heavy precipitation on government spending. However, expenditures of densely populated cities are less sensitive to temperature

changes. In addition, there is evidence indicating municipal adaptation to rising temperature over time.

The findings of this paper may be generalizable to other states, particularly those in New England. States in the New England region have similar climates, and some of their fiscal institutions share similar characteristics, such as school districts that are fiscally dependent and county governments (if they have any) that are weak. Therefore, it is plausible that the relationship between municipal spending and weather is similar across the region. A parallel study using data from a state or states from other parts of the country would be a worthwhile contribution to this line of research.



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Table 1: Baseline Regression Results, 1990-2019

	Total Expenditures	Public Works	General Government	Education	Police	Fire	Human Services	Culture and Recreation
<i>Temperature</i>								
Average Temperature (°F)	0.0323*** (0.00827)	0.0840*** (0.0188)	0.0577*** (0.0138)	0.0136 (0.0103)	0.0231 (0.0176)	0.0400* (0.0222)	-0.0617** (0.0274)	0.0268 (0.0231)
% Days with Maximum Temperature $\geq 90$ °F	0.00131 (0.00179)	-0.000683 (0.00420)	0.00650 (0.00413)	0.00366 (0.00242)	0.00530 (0.00411)	-0.00568 (0.00622)	0.00157 (0.00737)	-0.00673 (0.00526)
% Days with Maximum Temperature $\leq 32$ °F	0.00406*** (0.000936)	-0.00101 (0.00265)	0.00399* (0.00205)	0.00229* (0.00121)	-0.00275 (0.00244)	0.000710 (0.00460)	-0.0120*** (0.00416)	0.00720** (0.00312)
<i>Precipitation</i>								
Total Precipitation (Inches)	0.0000105 (0.000496)	-0.000230 (0.00105)	0.000174 (0.000867)	0.0000128 (0.000628)	0.00203** (0.000959)	0.00115 (0.00141)	-0.00187 (0.00269)	-0.000611 (0.00138)
% Days with Precipitation $\geq 1$ Inch	-0.00323 (0.00228)	0.00108 (0.00467)	-0.00375 (0.00419)	-0.00477 (0.00407)	-0.000899 (0.00402)	-0.000260 (0.00604)	0.0246** (0.0105)	-0.00146 (0.00685)
Total Snowfall (Inches)	-0.000106 (0.000117)	0.00168*** (0.000305)	0.000123 (0.000264)	-0.000471 (0.000341)	-0.000317 (0.000257)	-0.000322 (0.000579)	-0.000554 (0.000657)	0.000141 (0.000434)
% Days with Snowfall $\geq 1$ Inch	0.00420*** (0.00162)	0.00527 (0.00420)	0.00828** (0.00342)	0.00225 (0.00221)	0.00438 (0.00360)	-0.00299 (0.00709)	0.000560 (0.00920)	-0.00204 (0.00579)
N	10,500	10,500	10,500	10,500	10,410	10,080	10,470	10,410

*Source:* Author's calculations

*Notes:* Dependent variables are in log real per capita dollars. Regressions control for fiscal year fixed effects, municipality fixed effects, municipality-specific linear time trends, log real per capita equalized valuations, and log real per capita state grants. Standard errors are in parentheses and are clustered by municipality.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 2: Test for Sensitivity to Potential Measurement Error in Weather Variables

	Total Expenditures	Public Works	General Government	Education	Police	Fire	Human Services	Culture and Recreation
<i>Temperature</i>								
Average Temperature (°F)	0.0342*** (0.00878)	0.0850*** (0.0201)	0.0592*** (0.0147)	0.0149 (0.0110)	0.0266 (0.0184)	0.0465** (0.0233)	-0.0542** (0.0266)	0.0320 (0.0247)
% Days with Maximum Temperature $\geq$ 90 °F	0.00157 (0.00189)	-0.00160 (0.00438)	0.00749* (0.00452)	0.00396 (0.00272)	0.00567 (0.00462)	-0.00562 (0.00641)	0.00136 (0.00812)	-0.00666 (0.00584)
% Days with Maximum Temperature $\leq$ 32 °F	0.00400*** (0.000995)	-0.00101 (0.00283)	0.00466** (0.00221)	0.00204 (0.00132)	-0.00239 (0.00237)	0.00160 (0.00480)	-0.0148*** (0.00445)	0.00720** (0.00340)
<i>Precipitation</i>								
Total Precipitation (Inches)	0.000106 (0.000514)	-0.00109 (0.00113)	0.000268 (0.000923)	0.0000281 (0.000658)	0.00174* (0.00105)	0.00117 (0.00145)	0.000820 (0.00223)	-0.000567 (0.00134)
% Days with Precipitation $\geq$ 1 Inch	-0.00391 (0.00245)	0.000673 (0.00513)	-0.00356 (0.00451)	-0.00530 (0.00439)	0.000238 (0.00404)	-0.00143 (0.00642)	0.0216** (0.0105)	-0.00216 (0.00722)
Total Snowfall (Inches)	-0.000123 (0.000127)	0.00165*** (0.000336)	0.000150 (0.000287)	-0.000508 (0.000379)	-0.000192 (0.000274)	-0.000263 (0.000635)	-0.000783 (0.000713)	0.0000553 (0.000488)
% Days with Snowfall $\geq$ 1 Inch	0.00467*** (0.00170)	0.00406 (0.00437)	0.00958*** (0.00362)	0.00269 (0.00240)	0.00463 (0.00347)	-0.00253 (0.00762)	0.00783 (0.00881)	-0.00274 (0.00609)
N	9,750	9,750	9,750	9,750	9,660	9,420	9,720	9,660

*Source:* Author's calculations

*Notes:* Dependent variables are in log real per capita dollars. Regressions control for fiscal year fixed effects, municipality fixed effects, municipality-specific linear time trends, log real per capita equalized valuations, and log real per capita state grants. Standard errors are in parentheses and are clustered by municipality. The 11 largest municipalities, each of which has an area greater than 50 square miles, are excluded from regressions. Also excluded are 14 municipalities that each have an area greater than 25 square miles and a shape that least resembles a circle.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 3: Test for Sensitivity to Potential Measurement Error in Spending Variables

	Total Expenditures	Public Works	General Government	Education	Police	Fire	Human Services	Culture and Recreation
<i>Temperature</i>								
Average Temperature (°F)	0.0285*** (0.00671)	0.0745*** (0.0172)	0.0588*** (0.0140)	0.0130 (0.0108)	0.0248 (0.0166)	0.0400* (0.0228)	-0.0626** (0.0276)	0.0383* (0.0212)
% Days with Maximum Temperature $\geq$ 90 °F	0.000708 (0.00161)	-0.00169 (0.00421)	0.00534 (0.00404)	0.00220 (0.00227)	0.00198 (0.00394)	-0.00946 (0.00595)	0.00130 (0.00699)	-0.00688 (0.00530)
% Days with Maximum Temperature $\leq$ 32 °F	0.00460*** (0.000928)	-0.000302 (0.00273)	0.00434** (0.00209)	0.00256** (0.00128)	-0.00124 (0.00227)	0.00336 (0.00383)	-0.0106*** (0.00398)	0.00739** (0.00311)
<i>Precipitation</i>								
Total Precipitation (Inches)	-0.000347 (0.000495)	-0.000703 (0.00106)	0.0000803 (0.000886)	-0.0000382 (0.000661)	0.00133 (0.000875)	0.000450 (0.00147)	-0.00149 (0.00272)	-0.000579 (0.00141)
% Days with Precipitation $\geq$ 1 Inch	-0.00184 (0.00226)	0.00299 (0.00453)	-0.00289 (0.00434)	-0.00484 (0.00419)	0.00186 (0.00356)	0.00239 (0.00570)	0.0240** (0.00995)	-0.00158 (0.00693)
Total Snowfall (Inches)	-0.0000384 (0.000117)	0.00174*** (0.000309)	0.000271 (0.000263)	-0.000495 (0.000355)	-0.000204 (0.000254)	0.0000288 (0.000536)	-0.000816 (0.000662)	0.0000245 (0.000446)
% Days with Snowfall $\geq$ 1 Inch	0.00415** (0.00166)	0.00542 (0.00432)	0.00815** (0.00344)	0.00226 (0.00224)	0.00627* (0.00327)	0.00159 (0.00663)	0.00643 (0.00897)	-0.000724 (0.00586)
N	10,170	10,170	10,170	10,170	10,170	9,780	10,170	10,170

*Source:* Author's calculations

*Notes:* Dependent variables are in log real per capita dollars. Regressions control for fiscal year fixed effects, municipality fixed effects, municipality-specific linear time trends, log real per capita equalized valuations, and log real per capita state grants. Standard errors are in parentheses and are clustered by municipality. Eleven municipalities with a population smaller than 500 at any time during the FY1990-FY2019 sample period are excluded from regressions.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 4: Results from Weighted Regressions

## (a) Using Municipality Area as Weight

	Total Expenditures	Public Works	General Government	Education	Police	Fire	Human Services	Culture and Recreation
<i>Temperature</i>								
Average Temperature (°F)	0.0313*** (0.00908)	0.0812*** (0.0200)	0.0501*** (0.0139)	0.0178 (0.0128)	0.0183 (0.0229)	0.0440 (0.0279)	-0.0740** (0.0360)	0.0274 (0.0273)
% Days with Maximum Temperature $\geq 90$ °F	0.00236 (0.00214)	0.00348 (0.00464)	0.00763* (0.00434)	0.00259 (0.00288)	0.00779 (0.00493)	-0.000190 (0.00730)	0.00153 (0.00700)	-0.00592 (0.00623)
% Days with Maximum Temperature $\leq 32$ °F	0.00446*** (0.000964)	-0.000981 (0.00291)	0.00405** (0.00200)	0.00327** (0.00137)	-0.00280 (0.00315)	0.00100 (0.00498)	-0.00962** (0.00433)	0.00776** (0.00338)
<i>Precipitation</i>								
Total Precipitation (Inches)	0.000150 (0.000552)	0.000429 (0.00112)	-0.00000411 (0.000907)	0.000438 (0.000771)	0.00255** (0.00108)	0.000828 (0.00163)	-0.00418 (0.00388)	-0.000969 (0.00185)
% Days with Precipitation $\geq 1$ Inch	-0.00404* (0.00237)	0.00198 (0.00452)	-0.00411 (0.00463)	-0.00819 (0.00545)	-0.00199 (0.00484)	0.00298 (0.00682)	0.0343*** (0.0128)	0.00141 (0.00841)
Total Snowfall (Inches)	-0.0000788 (0.000134)	0.00174*** (0.000309)	0.0000585 (0.000270)	-0.000589 (0.000483)	-0.000446 (0.000283)	0.000139 (0.000632)	-0.000624 (0.000725)	-0.0000436 (0.000516)
% Days with Snowfall $\geq 1$ Inch	0.00353** (0.00174)	0.00586 (0.00479)	0.00740** (0.00361)	0.00310 (0.00252)	0.00234 (0.00506)	-0.00917 (0.00894)	0.00313 (0.0133)	0.00170 (0.00698)
N	10,500	10,500	10,500	10,500	10,410	10,080	10,470	10,410

## (b) Using Inverse of Coefficient of Variation of Station Count as Weight

	Total Expenditures	Public Works	General Government	Education	Police	Fire	Human Services	Culture and Recreation
<i>Temperature</i>								
Average Temperature (°F)	0.0320*** (0.00960)	0.0878*** (0.0208)	0.0529*** (0.0139)	0.0153 (0.0116)	0.0172 (0.0210)	0.0337 (0.0246)	-0.0518* (0.0298)	0.0214 (0.0260)
% Days with Maximum Temperature $\geq 90$ °F	0.00143 (0.00209)	-0.000444 (0.00442)	0.00728 (0.00447)	0.00274 (0.00319)	0.00717 (0.00558)	-0.00700 (0.00764)	0.00196 (0.00870)	-0.00651 (0.00601)
% Days with Maximum Temperature $\leq 32$ °F	0.00389*** (0.00101)	-0.00135 (0.00266)	0.00336 (0.00213)	0.00217 (0.00134)	-0.00447 (0.00285)	-0.000713 (0.00553)	-0.0131*** (0.00471)	0.00762** (0.00335)
<i>Precipitation</i>								
Total Precipitation (Inches)	-0.0000729 (0.000509)	-0.000356 (0.000989)	0.000212 (0.000893)	0.000128 (0.000717)	0.00212* (0.00114)	0.00127 (0.00156)	-0.00151 (0.00267)	-0.000835 (0.00136)
% Days with Precipitation $\geq 1$ Inch	-0.00378 (0.00251)	0.0000263 (0.00472)	-0.00493 (0.00447)	-0.00688 (0.00537)	-0.000727 (0.00479)	-0.0000284 (0.00698)	0.0254** (0.0116)	-0.00281 (0.00741)
Total Snowfall (Inches)	-0.000145 (0.000130)	0.00164*** (0.000318)	0.0000804 (0.000286)	-0.000634 (0.000480)	-0.000330 (0.000318)	-0.000546 (0.000665)	-0.000523 (0.000787)	0.000246 (0.000498)
% Days with Snowfall $\geq 1$ Inch	0.00349** (0.00162)	0.00434 (0.00439)	0.00735* (0.00376)	0.00239 (0.00244)	0.00258 (0.00439)	-0.00563 (0.00825)	0.00178 (0.0103)	-0.00257 (0.00622)
N	10,500	10,500	10,500	10,500	10,410	10,080	10,470	10,410

Source: Author's calculations

Notes: Dependent variables are in log real per capita dollars. Regressions control for fiscal year fixed effects, municipality fixed effects, municipality-specific linear time trends, log real per capita equalized valuations, and log real per capita state grants. Standard errors are in parentheses and are clustered by municipality.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 5: Test for Lagged Weather Effects

	Total Expenditures	Public Works	Education	Police
<i>Temperature</i>				
Average Temperature (°F)	0.0198** (0.00768)	0.0559*** (0.0168)	0.00269 (0.00827)	0.000523 (0.0142)
Average Temperature (°F), 1-year Lag	0.0266*** (0.00560)	0.0525*** (0.0126)	0.0263*** (0.00922)	0.0407** (0.0157)
Average Temperature (°F), 2-year Lag	-0.00151 (0.00603)	0.0148 (0.0140)		
% Days with Maximum Temperature $\geq$ 90 °F	-0.000629 (0.00208)	-0.00363 (0.00460)	0.00306 (0.00264)	0.00298 (0.00406)
% Days with Maximum Temperature $\geq$ 90 °F, 1-year Lag	-0.00150 (0.00201)	-0.00442 (0.00473)	0.00240 (0.00218)	-0.00214 (0.00398)
% Days with Maximum Temperature $\geq$ 90 °F, 2-year Lag	-0.00351* (0.00185)	-0.000433 (0.00455)		
% Days with Maximum Temperature $\leq$ 32 °F	0.00416*** (0.00116)	-0.000330 (0.00324)	0.00254* (0.00143)	-0.00334 (0.00263)
% Days with Maximum Temperature $\leq$ 32 °F, 1-year Lag	0.00202 (0.00145)	0.00752** (0.00356)	0.00312** (0.00141)	-0.00461** (0.00232)
% Days with Maximum Temperature $\leq$ 32 °F, 2-year Lag	-0.00133 (0.00122)	0.00191 (0.00322)		
<i>Precipitation</i>				
Total Precipitation (Inches)	-0.000592 (0.000537)	-0.000874 (0.00125)	-0.000270 (0.000612)	0.00170* (0.000927)
Total Precipitation (Inches), 1-year Lag	0.000304 (0.000499)	-0.000134 (0.00123)	-0.000658 (0.000743)	-0.000231 (0.00103)
Total Precipitation (Inches), 2-year Lag	-0.000160 (0.000448)	-0.000202 (0.00116)		
% Days with Precipitation $\geq$ 1 Inch	-0.000884 (0.00242)	0.00563 (0.00498)	-0.00326 (0.00380)	0.00201 (0.00387)
% Days with Precipitation $\geq$ 1 Inch, 1-year Lag	-0.00186 (0.00213)	0.00270 (0.00521)	-0.0000434 (0.00389)	0.00569 (0.00460)
% Days with Precipitation $\geq$ 1 Inch, 2-year Lag	-0.000189 (0.00205)	0.00404 (0.00436)		
Total Snowfall (Inches)	-0.000136 (0.000127)	0.00186*** (0.000337)	-0.000517 (0.000352)	-0.000488* (0.000268)
Total Snowfall (Inches), 1-year Lag	0.000179 (0.000127)	0.0000258 (0.000335)	0.000227 (0.000196)	0.000425 (0.000334)
Total Snowfall (Inches), 2-year Lag	0.000122 (0.000142)	0.00117*** (0.000358)		
% Days with Snowfall $\geq$ 1 Inch	0.00530*** (0.00181)	0.00471 (0.00476)	0.00255 (0.00254)	0.00633* (0.00381)
% Days with Snowfall $\geq$ 1 Inch, 1-year Lag	0.00407** (0.00203)	0.00782 (0.00498)	0.00290 (0.00311)	0.00944** (0.00388)
% Days with Snowfall $\geq$ 1 Inch, 2-year Lag	0.00388** (0.00191)	0.00196 (0.00490)		
N	10,500	10,500	10,500	10,410

Source: Author's calculations

Notes: Dependent variables are in log real per capita dollars. Regressions control for fiscal year fixed effects, municipality fixed effects, municipality-specific linear time trends, log real per capita equalized valuations, and log real per capita state grants. Standard errors are in parentheses and are clustered by municipality.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 6: Test for Heterogeneity of Weather Effects by Coastal Adjacency

	Total Expenditures	Public Works	General Government	Education	Police	Fire	Human Services	Culture and Recreation
<i>Temperature</i>								
Average Temperature (°F)	0.0305*** (0.00834)	0.0807*** (0.0188)	0.0543*** (0.0138)	0.0136 (0.0103)	0.0215 (0.0183)	0.0323 (0.0226)	-0.0663** (0.0285)	0.0202 (0.0235)
Average Temperature (°F) × Coastal Dummy	0.00295 (0.00218)	0.00307 (0.00713)	0.00243 (0.00563)	-0.00336 (0.00309)	0.0110** (0.00427)	0.0199*** (0.00692)	0.0169 (0.0116)	0.000896 (0.00686)
% Days with Maximum Temperature ≥ 90 °F	0.000637 (0.00183)	-0.000612 (0.00417)	0.00621 (0.00418)	0.00329 (0.00242)	0.00462 (0.00407)	-0.00569 (0.00621)	0.00197 (0.00730)	-0.00778 (0.00533)
% Days with Maximum Temperature ≥ 90 °F × Coastal Dummy	-0.000737 (0.00100)	-0.00728** (0.00356)	-0.00311 (0.00378)	-0.000885 (0.00154)	-0.000974 (0.00144)	-0.00805*** (0.00299)	0.000676 (0.00603)	0.000598 (0.00435)
% Days with Maximum Temperature ≤ 32 °F	0.00401*** (0.00103)	-0.00270 (0.00284)	0.00390* (0.00224)	0.00294** (0.00134)	-0.00361 (0.00257)	-0.00121 (0.00489)	-0.0140*** (0.00468)	0.00725** (0.00332)
% Days with Maximum Temperature ≤ 32 °F × Coastal Dummy	0.000135 (0.00107)	-0.00218 (0.00363)	-0.00286 (0.00245)	-0.00172 (0.00130)	0.000506 (0.00185)	0.00587** (0.00297)	0.0101** (0.00504)	0.000382 (0.00326)
<i>Precipitation</i>								
Total Precipitation (Inches)	0.000406 (0.000514)	0.000605 (0.00103)	0.000686 (0.000919)	0.000161 (0.000655)	0.00229** (0.000940)	0.00211 (0.00144)	-0.00151 (0.00267)	0.000359 (0.00144)
Total Precipitation (Inches) × Coastal Dummy	-0.00218*** (0.000488)	-0.00450** (0.00175)	-0.00337*** (0.00108)	-0.00163*** (0.000570)	-0.00130* (0.000734)	-0.00382*** (0.00114)	0.00155 (0.00232)	-0.00439*** (0.00140)
% Days with Precipitation ≥ 1 Inch	-0.00870*** (0.00270)	-0.00535 (0.00548)	-0.00971* (0.00496)	-0.00905* (0.00465)	-0.00608 (0.00485)	-0.00659 (0.00734)	0.0308** (0.0125)	-0.00832 (0.00823)
% Days with Precipitation ≥ 1 Inch × Coastal Dummy	0.0233*** (0.00442)	0.0321*** (0.0122)	0.0281*** (0.00830)	0.0190*** (0.00555)	0.0199*** (0.00662)	0.0293*** (0.00992)	-0.0278 (0.0176)	0.0313*** (0.0120)
Total Snowfall (Inches)	-0.0000602 (0.000129)	0.00165*** (0.000331)	0.0000290 (0.000312)	-0.000368 (0.000389)	-0.000302 (0.000302)	-0.000494 (0.000673)	-0.000761 (0.000775)	-0.0000952 (0.000496)
Total Snowfall (Inches) × Coastal Dummy	-0.000380* (0.000194)	-0.0000951 (0.000592)	0.000253 (0.000450)	-0.000337 (0.000286)	-0.000163 (0.000316)	-0.000563 (0.000717)	-0.000404 (0.000855)	0.000318 (0.000711)
% Days with Snowfall ≥ 1 Inch	0.00205 (0.00164)	0.00361 (0.00459)	0.00675* (0.00395)	0.000271 (0.00242)	0.00251 (0.00414)	-0.00601 (0.00801)	0.00173 (0.0103)	-0.00236 (0.00626)
% Days with Snowfall ≥ 1 Inch × Coastal Dummy	0.00956*** (0.00283)	0.00446 (0.00764)	0.00517 (0.00563)	0.00833** (0.00397)	0.00839* (0.00436)	0.0142 (0.00958)	-0.00160 (0.0120)	0.000593 (0.00916)
N	10,500	10,500	10,500	10,500	10,410	10,080	10,470	10,410

*Source:* Author's calculations

*Notes:* Dependent variables are in log real per capita dollars. Regressions control for fiscal year fixed effects, municipality fixed effects, municipality-specific linear time trends, log real per capita equalized valuations, and log real per capita state grants. Standard errors are in parentheses and are clustered by municipality. Coastal Dummy is an indicator variable for coastal adjacency. There are 78 coastal municipalities in Massachusetts.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$



Table 7: Test for Heterogeneity of Weather Effects by Population Density

	Total Expenditures	Public Works	General Government	Education	Police	Fire	Human Services	Culture and Recreation
<i>Temperature</i>								
Average Temperature (°F)	0.0315*** (0.00830)	0.0881*** (0.0188)	0.0594*** (0.0138)	0.0130 (0.0104)	0.0240 (0.0180)	0.0384* (0.0224)	-0.0643** (0.0279)	0.0241 (0.0235)
Average Temperature (°F) × Density Dummy	-0.00710** (0.00321)	-0.0212** (0.00863)	-0.0131 (0.00839)	-0.00704* (0.00385)	-0.00694 (0.00563)	0.00335 (0.00658)	0.00402 (0.0133)	0.00183 (0.00740)
% Days with Maximum Temperature ≥ 90 °F	0.00111 (0.00184)	0.000240 (0.00427)	0.00575 (0.00430)	0.00319 (0.00241)	0.00498 (0.00416)	-0.00482 (0.00634)	0.00108 (0.00745)	-0.00744 (0.00542)
% Days with Maximum Temperature ≥ 90 °F × Density Dummy	0.00128 (0.00126)	-0.00432 (0.00438)	0.00509 (0.00456)	0.00242 (0.00161)	0.00226 (0.00212)	-0.00560** (0.00256)	0.00110 (0.00655)	0.00237 (0.00405)
% Days with Maximum Temperature ≤ 32 °F	0.00417*** (0.000931)	-0.000695 (0.00262)	0.00443** (0.00207)	0.00233* (0.00120)	-0.00253 (0.00248)	0.000251 (0.00463)	-0.0124*** (0.00416)	0.00671** (0.00313)
% Days with Maximum Temperature ≤ 32 °F × Density Dummy	-0.00673*** (0.00150)	-0.00896* (0.00481)	-0.00655** (0.00333)	-0.00600*** (0.00135)	-0.00529** (0.00226)	-0.00330 (0.00258)	0.00169 (0.00711)	-0.00346 (0.00383)
<i>Precipitation</i>								
Total Precipitation (Inches)	0.000229 (0.000490)	-0.000489 (0.00102)	0.000105 (0.000874)	0.000132 (0.000636)	0.00209** (0.000932)	0.00146 (0.00142)	-0.00178 (0.00271)	-0.000254 (0.00140)
Total Precipitation (Inches) × Density Dummy	-0.00271*** (0.000749)	0.000911 (0.00279)	-0.0000431 (0.00173)	-0.00152** (0.000717)	-0.00120 (0.000969)	-0.00355*** (0.00104)	-0.0000501 (0.00373)	-0.00312* (0.00175)
% Days with Precipitation ≥ 1 Inch	-0.00445** (0.00226)	0.00265 (0.00486)	-0.00319 (0.00427)	-0.00505 (0.00418)	-0.00151 (0.00410)	-0.00176 (0.00624)	0.0250** (0.0111)	-0.00272 (0.00705)
% Days with Precipitation ≥ 1 Inch × Density Dummy	0.0198*** (0.00668)	-0.0162 (0.0222)	-0.00457 (0.0139)	0.00546 (0.00682)	0.0110 (0.00809)	0.0222** (0.00893)	-0.0104 (0.0344)	0.0159 (0.0161)
Total Snowfall (Inches)	-0.000100 (0.000119)	0.00182*** (0.000309)	0.000218 (0.000279)	-0.000474 (0.000351)	-0.000230 (0.000262)	-0.000254 (0.000604)	-0.000702 (0.000686)	0.000127 (0.000450)
Total Snowfall (Inches) × Density Dummy	0.000533* (0.000293)	-0.000653 (0.000774)	-0.000530 (0.000606)	0.000530 (0.000348)	-0.000259 (0.000387)	-0.000000389 (0.000527)	0.00118 (0.00121)	0.000704 (0.000701)
% Days with Snowfall ≥ 1 Inch	0.00384** (0.00163)	0.00472 (0.00417)	0.00691* (0.00360)	0.00230 (0.00230)	0.00322 (0.00391)	-0.00431 (0.00758)	0.00285 (0.00967)	-0.00180 (0.00610)
% Days with Snowfall ≥ 1 Inch × Density Dummy	-0.000253 (0.00351)	0.000473 (0.0106)	0.00911 (0.00635)	-0.00368 (0.00451)	0.00715 (0.00483)	0.00613 (0.00690)	-0.0187 (0.0122)	-0.00488 (0.00750)
N	10,500	10,500	10,500	10,500	10,410	10,080	10,470	10,410

*Source:* Author's calculations

*Notes:* Dependent variables are in log real per capita dollars. Regressions control for fiscal year fixed effects, municipality fixed effects, municipality-specific linear time trends, log real per capita equalized valuations, and log real per capita state grants. Standard errors are in parentheses and are clustered by municipality. Density Dummy is an indicator variable for a 30-year average population density greater than or equal to 3,000 people per square mile. There were 35 such municipalities in Massachusetts during the FY1990-FY2019 sample period.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 8: Test for Adaptation over Time

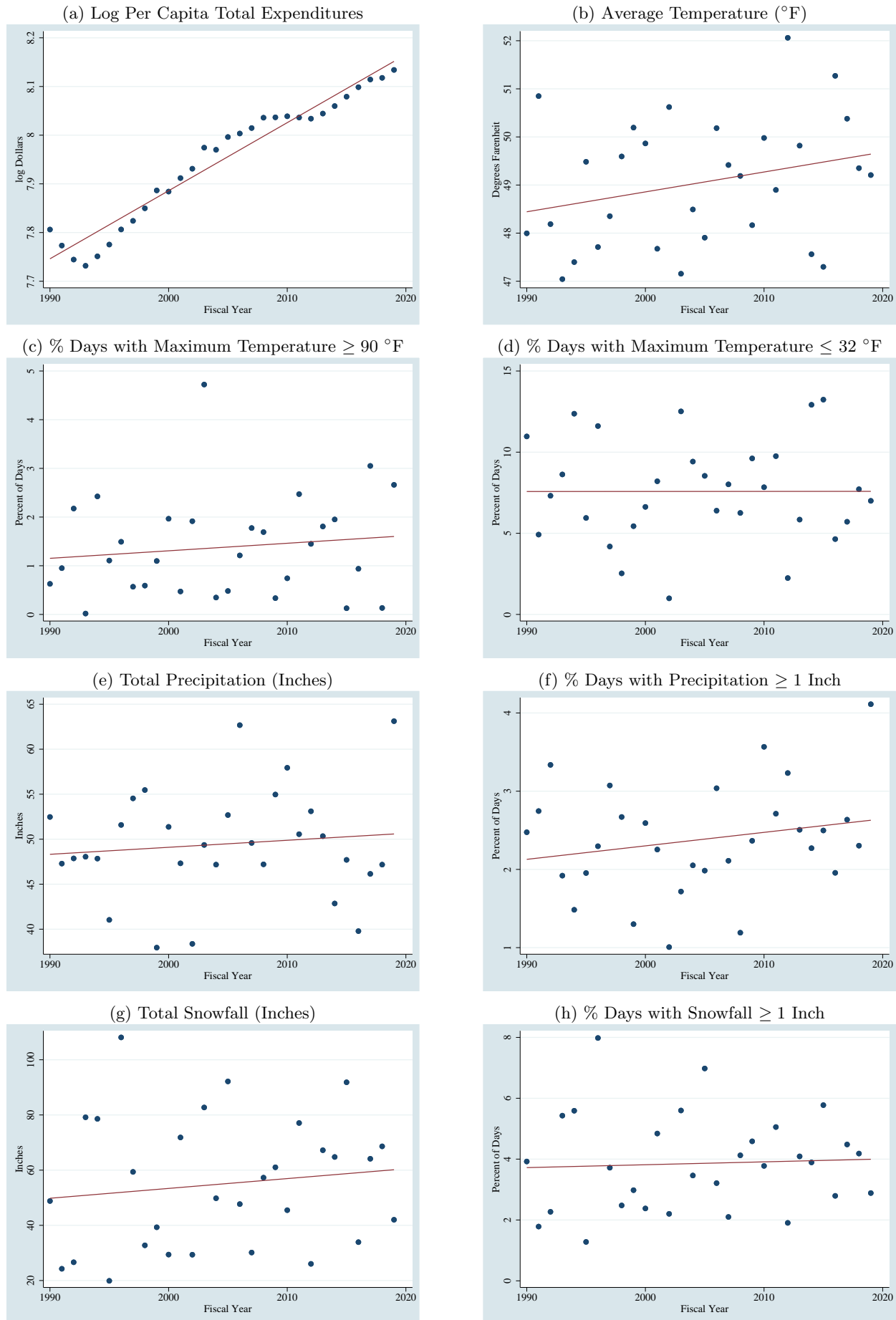
	Total Expenditures	Public Works	General Government	Education	Police	Fire	Human Services	Culture and Recreation
<i>Temperature</i>								
Average Temperature (°F)	0.0331*** (0.00839)	0.0814*** (0.0196)	0.0551*** (0.0149)	0.0128 (0.0102)	0.0157 (0.0177)	0.0349 (0.0249)	-0.0602** (0.0294)	0.0396* (0.0231)
Average Temperature (°F) × Dummy for 2005-2019	-0.0161*** (0.00574)	-0.0174 (0.0139)	-0.0142 (0.0116)	-0.0171** (0.00792)	0.0121 (0.0116)	-0.0145 (0.0184)	-0.0109 (0.0282)	-0.0290* (0.0163)
% Days with Maximum Temperature ≥ 90 °F	0.00225 (0.00277)	0.00218 (0.00660)	0.0130** (0.00613)	0.00439 (0.00390)	0.0121* (0.00735)	-0.00117 (0.00991)	0.00465 (0.0119)	-0.0122 (0.00976)
% Days with Maximum Temperature ≥ 90 °F × Dummy for 2005-2019	-0.00363 (0.00413)	-0.00675 (0.0101)	-0.0157* (0.00834)	-0.00261 (0.00596)	-0.0138 (0.00943)	-0.00794 (0.0146)	-0.00664 (0.0164)	0.00487 (0.0135)
% Days with Maximum Temperature ≤ 32 °F	0.00610*** (0.00175)	-0.00176 (0.00412)	-0.000643 (0.00419)	0.00477** (0.00237)	-0.0106** (0.00507)	0.000171 (0.00827)	-0.00377 (0.00820)	0.0154*** (0.00593)
% Days with Maximum Temperature ≤ 32 °F × Dummy for 2005-2019	-0.00510** (0.00210)	-0.00137 (0.00516)	0.00405 (0.00503)	-0.00545** (0.00261)	0.0111* (0.00634)	-0.00270 (0.00945)	-0.0140 (0.00976)	-0.0131** (0.00648)
<i>Precipitation</i>								
Total Precipitation (Inches)	-0.00126 (0.000817)	-0.000736 (0.00160)	0.00287** (0.00145)	-0.00176* (0.000982)	0.00164 (0.00145)	-0.00245 (0.00238)	-0.00445 (0.00389)	0.00300 (0.00218)
Total Precipitation (Inches) × Dummy for 2005-2019	0.00213** (0.000971)	0.000299 (0.00218)	-0.00352* (0.00181)	0.00182 (0.00126)	0.000571 (0.00169)	0.00701** (0.00345)	0.00424 (0.00491)	-0.00573* (0.00316)
% Days with Precipitation ≥ 1 Inch	-0.00572* (0.00325)	-0.00233 (0.00650)	-0.00473 (0.00574)	-0.0107 (0.00664)	0.00118 (0.00589)	0.00934 (0.00793)	0.0304* (0.0155)	-0.0168 (0.0107)
% Days with Precipitation ≥ 1 Inch × Dummy for 2005-2019	0.00496 (0.00385)	0.00963 (0.00910)	0.00353 (0.00857)	0.0145* (0.00799)	0.000211 (0.00731)	-0.0211 (0.0133)	-0.0143 (0.0190)	0.0279** (0.0140)
Total Snowfall (Inches)	-0.000148 (0.000236)	0.00139** (0.000585)	0.000814* (0.000460)	-0.00122 (0.000744)	0.000948** (0.000479)	-0.000432 (0.000859)	-0.00192* (0.00113)	-0.000174 (0.000787)
Total Snowfall (Inches) × Dummy for 2005-2019	-0.0000153 (0.000308)	0.000689 (0.000723)	-0.000606 (0.000572)	0.00121 (0.000813)	-0.00199*** (0.000559)	-0.0000812 (0.000977)	0.00173 (0.00145)	0.000783 (0.00107)
% Days with Snowfall ≥ 1 Inch	0.00315 (0.00248)	0.00705 (0.00608)	0.0128*** (0.00453)	0.00262 (0.00376)	-0.00669 (0.00668)	0.00172 (0.00812)	0.00764 (0.0141)	0.00347 (0.00826)
% Days with Snowfall ≥ 1 Inch × Dummy for 2005-2019	0.000646 (0.00326)	-0.00413 (0.00793)	-0.00959 (0.00613)	-0.000992 (0.00464)	0.0214** (0.00915)	-0.0145 (0.0118)	-0.0136 (0.0174)	-0.00877 (0.0100)
N	10,500	10,500	10,500	10,500	10,410	10,080	10,470	10,410

Source: Author's calculations

Notes: Dependent variables are in log real per capita dollars. Regressions control for fiscal year fixed effects, municipality fixed effects, municipality-specific linear time trends, log real per capita equalized valuations, and log real per capita state grants. Standard errors are in parentheses and are clustered by municipality. Dummy for 2005-2019 is an indicator variable for the second half of the sample period.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Figure 1: Massachusetts Municipal Spending and Weather Trends, 1990-2019



Sources: Massachusetts Department of Revenue and Global Historical Climatology Network daily

Notes: Yearly values are calculated as the average of the 350 municipalities in the sample. The red line in each plot represents a univariate regression on fiscal year. Yearly expenditure data are in 2019 dollars.