The Impact of Urban Sprawl on the Temperature in the United States, During the past four Decades

Golnoush Rahimzadeh

Department of Economics

Andrew Young School of Policy Studies

October 31, 2019

This Version: October 31, 2019

[Latest Version]

Abstract

Urban sprawl contributes to the heat island effect by eliminating vegetation, expanding dark surfaces, and increasing the daily travel distance. This study quantifies this effect by constructing and linking the required measures and exploiting variations in the data using different identification strategies to quantifies the causal relationship. I construct an index of residential compactness in U.S. metropolitan areas using satellite remote sensing and geographic information to analyze the landscape changes from 1974 to 2012 and link it to the Global Surface Summary of the Day (GSOD) data for the same period. To address the reverse causality issue (the effect of temperature differences on the horizontal development), I utilize the planned interstate highways, emanating from the central cities as an instrument for the sub-urbanization in the United States. I also add another layer of identification by introducing a control group for each MSA in the sample. The results suggest a positive and causal relationship

between the temperature of the MSA center and Urban sprawl. Thus, the horizontal development of the city imposes an extra burden on the temperature of the city center.

1 Introduction

The average temperature has increased in the past five decades in the United States and is expected to continue to rise.[1] Metropolitan areas are significantly warmer than their surrounding rural areas, a phenomenon known as an urban heat island(UHI). While in cities with a cold climate or in cold seasons the rise in temperature can be comforting, in relatively warmer climate and especially in summers this temperature rise has an undesired harmful effect on human health, economic productivity, and energy consumption. Urban climate features, such as temperature, are affected by the urban structure. A positive relationship between soil sealing and land surface temperature has been detected in many studies (Weng et al. (2007), Schueler (1994)). This relationship may suggest that urban sprawl can elevate the heat island effect both in geographic extent and intensity(Bhatta (2010)). Extending low-density suburbs changes the environment physically by eliminating vegetation such as tree cutting and by increasing dark surfaces like roads.

The association between urban sprawl and climate feature has been discussed in economic, urban planning and environmental science literatures. However, existing studies have at least

[1]The annual average temperature of the contiguous United States has risen since the start of the 20th century. In general, the temperature increased until about 1940, decreased until about 1970, and increased rapidly through 2016. In particular, annual average temperature over the contiguous United States has increased by $1.2°F(0.7°C)$ for the period 1986–2016 relative to 1901–1960. There is general consistency between Surface and satellite data in their depiction of rapid warming of past few decades. The annual average temperature of the contiguous United States is projected to rise throughout the century. Increases for the period 2021–2050 relative to 1976–2005 are projected to be between $2.5°F$ to $2.9°F$ (Zhongming et al. (2017))

one of the following shortcomings. First, they do not show the causal relationship between sprawl and climate variables. Second, they focus on small regions with specific characteristics and do not give a broad picture of the phenomenon. Third, they used a narrow definition of sprawl, or their temperature-related variables are limited, and as a result, they do not examine a various aspect of the phenomenon. Oke (1973) explored the relationship between city population and the intensity of the heat island effect in Montreal and found that areas with higher density are correlated with a grade of UHI effect. This is not a surprising result, as many of the factors that cause the UHI are stronger in more densely developed areas of a city. From a public policy point of view, the important question is whether to build vertically or horizontally. The answer in the literature depends on how the question asked because of the interdisciplinary nature of the question and how UHI is measured. Stone and Rodgers (2001), in a study on residential development patterns of Atlanta area at the parcel level suggest that lower density radiant patterns of residential pattern contribute in grade of UHI formation after controlling for downtowns and the radiative trapping. Stone et al. (2010) also measure the correlation between the mean annual change in the number of extreme heat days between 1956 and 2005 and the sprawl index of each region in 2000, where sprawl index measured by Ewing et al. (2003) study. Coutts et al. (2007) using data from multiple sites across Melbourne, and Martilli (2014), using simulation data suggest contradictive result that compact planning leads to less UHI formation.

I use U.S. conterminous wall-to-wall anthropogenic land use trends (NWALT), created in 2015 by U.S. Geological Survey (USGS). NWALT is a consistent and long-period independent time-series dataset that depicts land use and covers United State for five Waves between 1974 to 2012. I construct a panel data for analyzing sprawl based on actual expansion of 350 metropolitan areas for the first time.

To address endogeneity concerns and in particular reverse causality due to the changes in households relocation preferences derived by changes in temperature I utilize three different methods. I make a proper control group and employ Difference-in-Difference(DiD) approach assuming exogenous and continues policy in effect from 1972 to 1992. I also utilize the number of interstate highways in the national plan, emanating from the central city, as an instrument for sprawl. Thirdly, I add to the identification power of both of these two methods by combining multiple period DiD with IV setup. My finding suggests, for the middle size MSA's, 10 percentage point decrease in the residential compactness of MSA leads to about 1.1 degrees Farenheit increase in the annual mean temperature of the MSA center. This is resulted by utilizing combination of DiD and IV methods and while it shows smaller effect than DiD, its effect is larger than IV marginal effect.

The rest of the paper is organized as follows. After describing construction of urban sprawl in the following part, in section 2, I discuss estimation methods I utilize and different identification strategies. Section 3 discusses construction of two different data sources (weather data and scatteredness). Then in section 4, the results are presented. Section 5 introduces a new method for targeting proper control group and finally, I conclude in section 6. Results for the range of other atmospheric variables are analyzed in the appendix 1.

1.1 Measuring urban sprawl

Urban sprawl refers to a particular form of urbanization which associated with certain characteristics. The definition of sprawl that different study use differs base on the aspect of sprawl they focus, and the limitation in data and methods. Following characteristics has been widely associated with urban sprawl. First, low population density; high level of urbanized land per person; indicated inefficient land use. When in an area, the rate of urbanization is highly greater than the rate of population growth we are facing sprawling phenomenon(Black (1996); Freeman (2001); Galster et al. (2001); Harvey and Clark (1965); STPP 2000; Glaeser and Kahn (2004); Baum-Snow (2007); Ewing et al. (2003)). Second, leapfrogging; scattered development; refers to the building of new residences, either separately or in a subdivision, at some distance from existing built-up areas especially in the transition zone between urban and rural area. (Clawson (1962); Mills (1981); Gordon and Richardson (1997), Yeh and Li (2001), Burchfield et al. (2006), Ewing et al. (2003)) Third, Separate Land use is when employment and retail services are far apart from the residential area, which will increase driving.(Brown et al. (1998);Duany and Plater-Zyberk (2003); Ewing et al. (1994),Ewing (1997),Ewing et al. (2003)),America (2014); Galster et al. (2001)). Forth, Lack of street accessibility and connectivity, unplanned urban growth in suburb leads to inefficient street systems. (Duany and Plater-Zyberk (2003); NRDC 1996; Ewing 1994,1997, 2003,20014) Although the presence of sprawl may seem obvious, it is difficult to define and quantify urban sprawl. In fact, even though the sprawling city was a hot topic from early 1950, It was not properly quantified until recentlyMalpezzi et al. (1999)). Galster et al. (2001) review eight different measures of residential development grasp different dimension of sprawl such as density centrality, Proximity of land use, etc. They rank thirteen large U.S. cities base on six of these measurements.Ewing et al. (2003) estimated sprawl indices for 83 U.S. for change between 1990-2000 metropolitan areas using 22 variables1 that represent various aspects of development patterns. They focus on 4 different dimension of sprawl Residential Density, Land Use Mix, Degree of Centering and Street Accessibility, arguing that one factor cannot capture complexity of sprawl. And while some cities like Atlanta sprawl in all dimensions and some other like NY compact in all factors; other cities are not consistent with all factors. To construct sprawl index for each dimension. They combined up to seven variables via principal component analysis into one factor representing the degree of sprawl in each dimension. This factor was then normalized such that the mean value is 100, and the standard deviation is 25. America (2014) update this result for 221 metropolitan area in 2010. Unfortunately, most of the variable they used does not exist before 1990. Thus, while their index can be used for measuring stock of sprawl, it cannot be used to capturing sprawl trend throughout years. Comprehensive list of variables used in this study helps to understand several aspects of sprawl, however reducing these dimensions to one index involve some degree of information loss. For studying the effect of sprawl is important to have a clear idea which factor plays a role.

Glaeser and Kahn (2004) use variety of measures to capture sprawl focusing mostly on population density and separation of use. Percentage of Population density and job density (Within Inner 3 and 5 Mile Ring and MSA) and Median Person's Distance in Miles from the Central business district. They also report that the correlation between different measures can be very low.Angel et al. (2005) use classifying satellite images of cities in 1990 and 2000 to directly examining the expansion form of cities. They used population density as the main variable of interest, but their Index of population density has a strong point comparing previous studies. Instead of administrative boundaries, they measure the actual built-up area of the city. Using Administrative boundaries does not allow reliable comparisons between cities. So, the resulting population density is sensitive to the definition of boundaries which vary even within the United States. Another weakness of using average population density is it neglects the distributional aspect of the metropolitan population. Burchfield et al. (2006) focus on capturing the extent to which residential development in urban areas is scattered. Like Angel et. all. Their methodology is analyzing landscape change with satellite remote sensing and Geographic Information System. And They use Land cover and Land use data from Landsat 5 Thematic Mapper satellite imagery and high-altitude aerial photographs. This may consider as a shortcoming of their research. Since two different datasets may not be compatible with each other(Irwin et al. (2006)) Their data contains square cells of 30 by 30 meters situated on a regular grid. Every cell predominant land cover was assigned Land Cover Codes such as Residential development, Water, Forest, etc. To measure the extent of sprawl, for each 30-meter cell of residential development, they calculate the percentage of open space in the immediate square kilometer. They compute the Sprawl index as a change in the average undeveloped land across all residential development in each metropolitan area. They also introduce the stock of development in 1976 and in 1992 by doing the same calculation that gives Percentage of land not developed in the square kilometer surrounding residential areas for 1976 and 1992. They discuss the correlation of their measure with other measures such as Median Lot Size, Miles Driven per Person and share of Employment over 3 miles from CBD and conclude that while scatteredness is a key factor of sprawl, it does not grasp all dimension of it. Specifically, they find a low correlation between their measure and centralization employment. This study aims to use Datasets obtained through remote sensing to construct the measure for urban sprawl. The first reason is remote sensing datasets consistent over great areas and over time which allows us to construct panel data. The second reason is that remote sensing allows us to measure the expansion of the built-up area of cities directly. Following Burchfield et al. (2006) I measure residential pattern using land use data and by taking the average value across all residential cells within a metro region construct to construct an Index for sprawl. As I discussed, the first two characteristics of sprawl namely low population density and scattered development are often found not to be correlated with the second two characteristics which are separate land use and lack of street accessibility. To make the effect of these characteristics distinguishable, instead of measuring the ratio of open space in each cell's neighborhood we measure residential area and commercial area separately. We also expand Burchfield et al. (2006) work and construct a panel dataset for 363 metropolitan area for 1974 ,1982, 1992, 2002 and 2012.

2 Estimation

2.1 Identification Strategy

To identify the effect of horizontal urban development on inner city temperature, one has to consider the reverse causality problem that emerges when temperature change of the inner city or suburb affects an individual's preference and hence decision to relocate in or out of the city centers. To improve identification power and detect the causal effect instead of correlation structure, I employ three different strategies, namely Diff-in-Diff, Instrumental Variable, and combination of these two methods in a panel study of the U.S. MSAs.

2.1.1 Diff-in-Diff

One approach for reducing the reverse causality is Difference-in-Difference (DiD), which is developed from Randomized Controlled Trial (RCT) literature. I use the development of highways in the united states as an intervention or policy change. Alonso et al. (1964) in their land use model suggests households consider a combination of rent and transportation costs as the price of housing. Hence the development of highways should shape the new subs as households decide to relocate and optimize their utility. However, the development of highways can be used as an intervention only if it is exogenous. Following Baum-Snow (2007) and Duranton et al. (2014), it can be argued that since the development of new highways was based on national defense and trade needs, requiring the shortest possible distance to connect MSA centers, it's map is not based on households preferences. This plan for the development of highways took about 40 years to be completed and was finished by 1992. I have data as early as 1972 (wave 1) and hence use it for pre-intervention. I also use Wave 4 (Years 2000 to 2004) as a post-intervention period to allow households to relocate after completion of highways in Wave 3 (1990 to 1994). To have DiD framework fully operational, I also need a valid control group. I choose a region close enough to each MSA center so that it reflects MSA's characteristics but is not being affected by the development of highways and consecutively urban developments. Hence I estimate the following regression model:

$$Y_{it} = \beta_0 + \beta_1.Post_{it} + \beta_2.Treated_{it} + \beta_3.Post_{it}.Treated_{it} + X_{it}.\beta_4 + \epsilon_{it} \tag{1}$$

where, Y_{it} is outcome for MSA i at period t (1972-1976, and 2000 - 2006), $Post_{it}$ refers to a dummy indicating one if it is post-intervention and zero otherwise, $Treated_{it}$, determines if observation belongs to treated group (MSA center) or control group (MSA surrounding area). DiD coefficient is β_3 where it compares the partial correlation between post-intervention for the treated group and pre-intervention for the control group. I control for other characteristics by X_{it} which is a vector of time-varying, MSA specific variables. Lastly, ϵ_{it} is a gaussian error that enables the utilization of simple OLS for this regression.

2.1.2 Instrumental Variable

Another way to address the reverse causality problem is to employ Instrumental Variable. I use an exogenous source of variation in highways as an instrument for sprawl. As discussed in the previous section, highways are likely to affect sprawl as a consequence of the decreased transportation cost. This insight is founded on the theory, developed by Alonso et al. (1964) for land use. According to their model, households consider a combination of rent and transportation costs as the price for housing. Thus, if transportation costs were lower, then the demand for space in the suburbs relative to central cities increases. Baum-Snow (2007) empirically tested the hypothesis that highways contribute to growth in the suburban population compared to the central city. As noted by Baum-Snow (2007), in testing such a hypothesis, one might be concerned by reverse causation if urban patterns affect the location of highways. To address this concern Baum-Snow (2007) and Duranton et al. (2014) use the national plan of highway routes proposed in 1947 as an instrument for highway rays. Since the planned portion of the interstate highways was required to serve national defense and trade, the number of rays in the 1947 national plan is a valid source of exogenous variation highways. According to Public Roads Administration press release in 1947, the interstate plan was designed to connect principal metropolitan areas, cities, and industrial centers by routes as direct as it was practicable to serve the national defense and to connect suitable border points. Baum-Snow (2007) used the highway plan as an instrument for highways and found a causal connection between highways and sprawl. Continuing through this line of reasoning, as the planned portion of highways affects sprawl and scatteredness of residential distribution, and residential distribution affects temperature, I can test the null hypothesis of no causal effect of sprawl on the temperature of MSA's center by instrumenting for residential distribution. Hence, cutting out the middle step, I use the planned portion of highways as an instrument for sprawl in causal analysis of the effect of sprawl on UHI. I calculate the time series of rays by multiplying the number of rays in the 1947 plan and the fraction of federally funded highway mileage in the 1956 Federal Aid Highway Act completed at each point in time. For the first stage in my two-stage IV, I have:

$$Sprawl_{it} = \alpha + \beta PlannedHW_{it} + \theta Z_i + d_i + \epsilon_{it}, \tag{2}$$

where $Sprawl_{it}$ is the sprawl index(discussed in detail below), Z_i is the vector of control variables, d_i is MSA specific fixed effects that point out the utilization of panel data, and $PlannedHW_{it}$ is the planned portion of interstate highways. Note that I use planned portion of high ways instead of completed portion following Baum-Snow (2007), to control for the reverse causality between completed highways and residential distribution through MSA as it may affect the completion speed and allocation of funds. Completting first stage, I can use predicted value of the measure of sprawl in the second stage:

$$Y_{it} = \delta + \theta Spr\hat{a}wl_{it} + \lambda Z_i + e_{it}, \tag{3}$$

where, Y_{it} represents a temperature related variable such as the annual mean temperature of the MSA's center.

One also could use three-stage IV, where the first instrumenting planned portion for the completed portion of highways. Then predicting the sprawl index by predicted completed portion of highways and finally, using the predicted measure of sprawl to analyze the causal effect of sprawl on the interested outcome. As the source of exogenous variation is the same in both two and three-stage IV models, I expect to see no difference in the evaluation of the interested causal effect and hence use two-stage IV here.

2.1.3 Hybrid Model

While exploiting exogenous variations, introduced by the instrumental variable, can resolve the endogeneity problem of reverse causality, one always can question the exogeneity of the instrument if not it's independence from the outcome. On the other hand, while DiD approach needs fewer assumptions and hence provides more stable causal relationship, it suffers from lower identification power as it relies on the assumption of the homogeneity in the population and as a result, unbiased estimate of causal relationship requires independency between unobserved heterogeneity and the interested DiD coefficient. To exploit the stability of DiD and more identification power of IV approach provided by the panel structure, I integrate IV and diff-in-diff strategies. I approach this problem by setting a control observation for each treated one as it was explained in DiD section. I assume the temperature of MSA's surrounding area can be seen as a control for the temperature of inner city for each MSA. Since the distance between inner and surrounding areas are relatively short, the control group can reflect the same unobserved heterogeneities of the inner city area. Secondly, for the second difference, I exploit the exogenous variations by my instrumental variable, planned highway's ray. Assuming planned highway affects the residential scatteredness exogenously, I have a policy change (exogenous variation) for each MSA-year and hence can employ the diff-in-diff identification strategy. The combination of IV and diff-in-diff adds to the identification power by the factor of the number of MSAs, multiplied by the number of waves. Hence I expect the causal relation is much more reliable in this framework. However, to make sure two identification strategies are working in accordance with each other, exogenous variation from IV should not affect my control groups (temperature of surrounding areas). The combination of IV and DiD also allows for exploiting the panel data feature to control for individual fixed effects. The individual fixed effect can provide some degrees of identification power due to the fact that it reduces the chance of unobserved heterogeneity bias. In other word, if there is a fixed characteristic associated with an observation (for example, elevation), I do not need to control for it since it is reflected in individual fixed effect. Other characteristics which are variable through time then can be controlled by diff-in-diff setup where I have a control observation for each inner-city point in time. The first stage of the two-stage panel IV is the same as the first stage of the two-stage

IV, which was explained previously:

$$Sprawl_{it} = \alpha + \beta PlannedHW_{it} + \theta Z_i + d_i + \epsilon_{it}, \tag{4}$$

Definitions of variables here are the same as equation 2. In the second stage, instead of using the temperature of the inner city or MSA's center, I use the difference between the temperature of the MSA's center, and it's surrounding area or using DiD terminology, treated and control group. The definition of these groups is the same as explained in DiD section. Thus, the second stage of the two-stage IV is:

$$\Delta(Y_{it}) = \delta + \theta Spr\hat{a}wl_{it} + \lambda Z_i + e_{it}, \tag{5}$$

Here, Δ refers to the difference between interested outcome in and out of the MSA's center. Since the main focus of this study is to address the UHI effect, I continue using temperature as the outcome Y. The setup here allows for the panel regression techniques such as first difference and fixed-effect, where both of them help to control for individual unobserved heterogeneities.

3 Data

3.1 Scatteredness

I use U.S. Conterminous Wall-to-Wall Anthropogenic Land Use Trends (NWALT) which gives a U.S. national 60 m, 19-class mapping of anthropogenic land uses for five time periods. NWALT is compiled using existing data sources including NLCD 1992, 2006, 2011 and USDA Census of Agriculture, 1974–2012 and Spatial Analysis for Conservation and Sustainability (SILVIS) 1970-2000. The advantage of using NWALT is that it captures major land use trends by employing a consistent method for all years to represent an accurate land use. Burchfield sprawl can be defined as the ratio of undeveloped cells in a neighboring circle with a radius of 560 meters, centered at a residential cell, averaged over all the residential cells across MSA. In this study, I use the same method following procedure that involves assigning the percentage of residential area around each residential cell (with a radius of 1 km) and then averaging over all the assigned percentages in MSA. The procedure is as follows:

1. For every residential cell $i \in I_k$ where, I_k is the set of all the residential cells in A_k , count all the residential cells in a circle with radius of one km around i:

$$Count_i = \sum_{j \in J} 1[j = residential] \quad \forall i \in I_k$$

   Where $Count_i$ is the total number of the residential cells around residential cell i, $1[.]$ is an indicator function that equals 1 if a cell j around residennntial cell i occurs to be residential and 0 otherwise, and J is the set of all cells in a circle with radios of one km around residential cell i.

2. Divide $Count_i$ by the total number of cells in the circle around cell i

$$rc_i = \frac{Count_i}{|J|} \quad \forall i \in I_k$$

   Where, rc_i is the residential compactness ratio calculated for cell i, and $|J|$ is the norm of the set J.

3. Average over all the rc_i's in MSA_k results the Residential Compactness index for the MSA_k To calculate the relevant measures of residential compactness as described, I use ArcGIS software. Construction of the RC_k for Atlanta Metro area is shown visually in **Figure** F-1 through F-3.

$$RC_k = \frac{\sum_{i \in I_k} rc_i}{|I_k|}$$

Using the same procedure, I also introduce the second index for measuring sprawl. This index calculates the percentage of the commercial area around each residential cell (with a radius of 5 km) and then takes the average over all the residential cells for each MSA. This Measure captures the separate land use or employment accessibility that Both Glaser (2004) and Burchfield et al. (2006) find nearly uncorrelated with the residential distribution indexes which are designed to measure the sprawl. The procedure follows:

1. For every residential cell $i \in I_k$ where, I_k is the set of all the residential cells in A_k , count all the residential cells in a circle with radius of five km around i:

$$Count_i = \sum_{j \in J} 1[j = commercial] \quad \forall i \in I_k$$

Where $Count_i$ is the total number of the commercial cells around residential cell i, $1[.]$ is an indicator function that equals 1 if a cell j around residential cell i occurs to be commercial and 0 otherwise, and J is the set of all cells in a circle with radios of five km around residential cell i.

2. Divide $Count_i$ by the total number of cells in the circle (radius of 5 km) around cell i

$$ca_i = \frac{Count_i}{|J|} \quad \forall i \in I_k$$

To calculate the relevant measures of commercial accessibility as described, I use ArcGIS software. Construction of the RC_k for Atlanta Metro area is shown visually in **Figure** F-4 Where, ca_i is the commercial accessibility ratio calculated for cell i, and $|J|$ is the norm of the set J.

3. Average over all the rc_i's in MSA_k constructs the commercial accessibility measure for the MSA_k

$$CA_k = \frac{\sum_{i \in I_k} rc_i}{|I_k|}$$

To Identify urban area, I first found the central business district(CBD) as a point with highest commercial accessibility ratio in each MSA. and then define a circular bound around it that identifies inner city area.**Figure** F-5 and F-6 shows this visually for sample of the data.

3.2 Temperature Data

I use GSOD (Global Summary of the Day) data for years 1972-76, 1980-84, 1990-94, 2000-04 and, 2010-14 (twenty-five years) to calculate desired statistics such as annual and seasonal average temperature. GSOD data provides 18 surface meteorological elements which are driven using the hourly observations which are part of USAF DATSAV3 Surface data and Federal Climate Complex Integrated Surface Data (ISD). Historical data are available from 1929, but data has better quality for years after 1973, in terms of the number of stations and the average number of reported days per station. To make a daily observation a minimum of four observations are needed for the day. Thus, for station-days with less than four observations, GSOD reports missing. Other causes of missing observation are data restrictions or communications problems. For this study, we use only one year (1972) of the earlier part of the GSOD with less quality. For the year 1972, we only observe 53 stations, as opposed to the on average 394 stations per year. As a result, some of weather observatory stations that I use is different in each year and station can stop working for some years. I include a station-year in my data if it occurs to be inside an MSA boundary for that particular year. The Number of stations which are included in data and their changes is summarized in **Table** T-1. The number of stations increases from 394 to 900 on average, for years after 2010. Also, for every station-year that is available, weather information of 340 days is reported on average. I use all the available data that sums up to 4,228,407 station-days. Then for each station, I make statistics such as annual and seasonal mean, standard error, maximum and minimum of temperature.

3.3 Assigning Temperature to MSA Center

As mentioned before, temperature data is station-year specific, and I need a method to assign the acquired temperature from station to a particular MSA center. Knowing the MSA center's geographic coordinates (Latitude and Longitude) by the construction and acquiring those of the stations from GSOD data, I can calculate the distance between every pair of station and center. For this purpose, I use a planar approximation and limit the distances to less than 250 km. Two deficiencies of planar approximation are where first, the distance between two points becomes high and second, one or both points become close to the geographic pole. I do not have the second problem since the northernmost latitude in the contiguous United States is 49.38407°N. Also, limiting the search area to the circle with 250 km solves the first problem. I project the latitude and longitude coordinates onto plane assuming the spherical earth, and using the formula:

$$D_{ijt} = \sqrt{((\cos \frac{\pi}{180} y_{it}) \times 111.321 \times \Delta x_{ijt})^2 + (\Delta y_{ijt})^2} \tag{6}$$

Formula is receiving x_it and x_jt as the longitude of the MSA center i and station center j in period t in degrees, and y_it and y_jt as latitudes in degrees. Then, it calculates the distance between MSA center i and station j in kilometers (D_ijt). Also, formula corrects for the variation in distance between meridians (longitudes), with latitude. This problem occurs when the distance between two points on two different longitudes and on the same latitude is shrinking as we go closer to one of the poles and further from the equator. This formula also helps us to avoid the computational burden caused by assuming non-spherical earth in the other formulae.

Having the distance in km, between MSA center and all stations in a radius of 250 km, I calculate the average temperature of stations which are in a circle with particular radius r, centered at the MSA center:

$$IB\bar{T}_{it|r} = \frac{\sum_{j \in J_{i|r}} c_{jt}}{|J_{i|r}|} \tag{7}$$

Where $(IB\bar{T}_{it|r})$ is the average temperature assigned to the MSA center i in period t, using radius r, and is called Inner Bound Temperature (IBT), c_jt is the seasonal or annual statistics related to temperature (Mean, Max, Min) in station j and time t, J_{ir} is the set of all stations in the radius r of MSA center i and $|J_{ir}|$ is the norm of the set J_{ir}.

To pursue the goal of the current study in analyzing the heat island effect, I further need to assign another temperature to the area around the MSA center that represents the suburb of the center. I call this second temperature, the Outer Bound Temperature (OBT). I calculate OBT using:

$$OB\bar{T}_{it|rR} = \frac{\sum_{j \in J_{i|rR}} c_{jt}}{|J_{i|rR}|} \tag{8}$$

Where $OB\bar{T}_{it|rR}$ is the mean temperature of the stations in the surrounding areas of MSA center i, at time t, using an inner radius of r and outer radius R. Also, $J_{i|rR}$ is the set of all stations located in distance between r and R to the MSA center. c_jt is the temperature of center j at time t and $|J_{i|rR}|$ is the norm of the set $J_{i,rR}$. **Figure** F-7 shows the location of weather station to metropolitan area for sample of the data.

3.4 Setting Bounds

Metropolitan Statistic Area (MSA) is a geographic area with high population concentrated in its core and surrounding areas with economic ties to the core. A Metropolitan Area requires a Census Bureau urbanized area of at least 50,000 population. This definition can result in an enormous heterogeneity among MSAs. Furthermore, one particular MSA, might grow or diminish in size through time. As a result, using only one fixed Inner radius r and outer radius R for all MSAs might be problematic due to the urbanized area differences between small and big MSAs and through time for one specific MSA. I approach this problem by introducing Flexible bounds that involves assigning the radius r_it and R_{it} to different MSAs in different periods. I define both radii r_{it} and R_{it} as a function of the Total Number of

Residential Land Cells ($TRLC_{it}$) in each MSA i at time t:

$$r_{it} = \frac{\sqrt{\frac{TRLC_{it}}{\pi}}}{\frac{\sqrt{\frac{TRLC_F}{\pi}}}{r_F}} \quad , \quad R_{it} = \frac{\sqrt{\frac{TRLC_{it}}{\pi}}}{\frac{\sqrt{\frac{TRLC_F}{\pi}}}{R_F}} \tag{9}$$

The formula considers the fact that since TRLC is the area of the residential land, the radius can be calculated from $TRLC$ using the formula for the circle area ($Area = \pi \times r^2$). Then this radius which represents the numerator of both formulae above, is adjusted by the scaling parameter in the denominator:

$$\frac{\sqrt{\frac{TRLC_F}{\pi}}}{r_F} \quad , \quad \frac{\sqrt{\frac{TRLC_F}{\pi}}}{R_F} \tag{10}$$

Both of them calibrated from the average of the LC_{it} , r_{it} and R_{it} of the MSAs with distinctive Inner and Outer radiuses. I calibrate them using the numbers, shown in **Table 1**:

Table 1: Calibrated values to being used in Flexible Bound Scheme

$TRLC_F$	r_F	R_F
800000	50	150

While Numerator of the functions allows for the variations in bound between MSAs with varied sizes, the denominator scales the bound to an agreeable size.

For the fixed bound scheme, I use the radius suggested by flexible scheme formula for the first period tha MSA is observed and then keep the radius constant through time. This allows to reduce the heterogeneity between MSAs, however changes through time will not be reflected by this fixed measure.

4 Estimation Results

In this section, I discuss the results of the two schemes: fixed and flexible bounds. I follow each by sensitivity analysis.

4.1 Estimation Sample

Estimation sample is selected based on the rationale that suggests, MSAs which are already developed and very small MSAs do not contribute to any of the results. **Figure** G-1 shows the distribution of the residential compactness for each category of MSA size, divided into four categories, approximately represents quartiles of MSA size distribution. It suggests relatively larger MSAs are more likely to be residentially compact, and hence it is less likely for them to be developed. Most of these large MSAs are located by the sea and are at the intersection of the major trade routes, and hence the development of new highways is unlikely to affect them. On the other hand, for the smallest MSA group, their residential compactness measure is relatively smaller, suggesting these MSAs are horizontally developed, and any development in them is toward vertical development. However, based on the sample, these MSAs do not reach the vertical development level of the 50% middle MSAs by year 2014, which is the last year in the sample. These smaller MSAs also located near the sea, and it appears excluding either the MSAs near seashore or keeping the middle 50% reaches the approximately same result. **Figure** G-2 shows changes in the adjusted[2] measure of residential compactness for each of the three categories of smallest 25%, middle 50 % and upper 25% MSAs.

4.2 Fixed and Flexible bounds

Bounds are determined by a radius that itself is a function of MSA's residential counts. In fixed bound scheme, this residential count is fixed at the level it is when MSA is observed for the first time in data (1972). However, the flexible bound scheme allows for the radius to get updated every time the residential count is renewed. While fixed bound scheme is more rigid and is prone to the risk of invalidity when MSA is growing or shrinking severely. In the case of growing MSA out bound may be affected by the new horizontal development

[2]Adjustment is to make a ratio from the count of the raster points each representing residential land and total area in MSA.

and, hence, the control group is no more controlled and get treatment. On the other hand, while flexible bound scheme provides more stable and reliable control group, interpretation of the results, which are produced using this scheme is more difficult as control group is not attached to a specific geographical area, and geographical area moves in time to reflect the control group, close enough to represent features of the MSA center and yet not be affected by the changes in the MSA residential area. In **Figure** G-3 and **Figure** G-4 distribution of distances from the center of the MSA to the centroid of the weather stations in in-bound and out-bound areas are shown for both schemes. Two schemes show divergence in the common domain between in and out-bound distances. While in fixed scheme, two distributions are almost separable in the domain, in flexible bound scheme two distributions share a considerable domain. This is due to growth in some of the MSAs that makes their in-bounds stretch to the right where previously was dedicated to the out-bound. This stretch in distribution is more apparent in comparison between **Figure** G-5 and **Figure** G-6. It also shows, while in-bound moves in the flexible bound scheme, out-bound is moving further away. **Figure** G-7 and **Figure** G-8 shows even though flexible scheme allows for stretching of the bounds, the overall shape of the distribution of the distance between in and out-bound is preserved, except for the far right tail of the distribution. Finally, to have a better grasp of the changes through time, **Figure** G-9 provides growth of the inner-bound radius for selected group of major cities/MSAs. While all growing by time, New York grows slowest among the group and Atlanta grows fastest. It is partially due to the fact that New York was already developed both horizontally and vertically and, hence, there are not much extra space for horizontal development. Starting with the static bound scheme, I set the inner and outer radiuses to be 50 and 90 kilometers respectively. As a result inner bound contains all stations from the center to the value of the function of inner radius $f(50)$. Then out-bound includes stations which are between $f(90)$ and $f(150)$ kilometers away from the MSA center. Note that changing the radius may affect the number of stations that exists inside the bound and outside the bound for each MSA-year. Since we are interested in finding the effect of residential compactness on the heat island effect, it is vital to our analysis to have enough number of stations in both, in and outside of the bound. As it is shown in **Figure** G-7 ,the mass of the data is almost equally divided between in and out of the bound. The number of MSAs with available data temperature outside of the bound is 7842, and those with the available data for the temperature inside the bound are up to 7234 observations in 25 years. The Number of the MSAs with both inside and outside available temperature data sums to 6715, and considering for 25 years, it is approximately 268 MSAs per year. This number then will be reduced when we incorporate the Instrumental Variable since IV is not available for all the MSAs. **Table** 2 provides the Average distance between existent stations in outside and inside the 50 kn bound and CBD for all years.

Table 2:

	Number of MSAs	Average Distance
Inside of the Bound	7,234	24.98
Outside of the Bound	7,842	106.15

Number of MSA's and Average distance between center and In/Out-bound stations

4.3 Biased Estimates

I use the analysis of the biased estimator to identify the direction of the reverse causality later when I introduce unbiased estimators. Shown in the **Table** T-2 increase in the Residential Compactness from 0 to 1 (full range jump in the RC ratio) reduces the annual temperature of the MSA center by about 12 degrees Fahrenheit annually. This decrease in temperature is more severe during Winter and Autumn. Residential Compactness is moving against residential scatteredness or sprawl and hence, negative correlation is in accordance with the UHI hypothesis. These are biased estimator, suffering from different types of endogeneities. Reverse causality bias channels the effects from temperature of the MSA center to the residential compactness by affecting household preferences and hence, their decision to relocate in city suburbs or the city center. While factors such as gasoline price may discourage households from moving away from business centers (MSA center), other factors such as avoiding crowded places and possible lower utility price in suburbs may encourage them to relocate to suburbs.

4.4 Correction for unobserved fixed heterogeneity

One important source of endogeneity is the unobserved heterogeneity endogeneity. This problem can be reduced considerably by employing panel data and estimation techniques which drop fixed individual heterogeneity in the process of estimation and, hence, reducing unobserved heterogeneity bias to the individual, time-varying factors which are not orthogonal to the error term. I utilize fixed-effect panel estimation method that assumes Gaussian error structure and cancels out individual fixed effects. **Table** T-4 shows the same result in the previous section and instead of simple OLS coefficients, it reports fixed-effect coefficients. In summary, coefficients of warmer seasons (summer and spring) are less negative and coefficients of the colder seasons moved positively, to the degree that winter coefficient is completely positive. The overall annual effect is less negative compared to the OLS estimation. It suggests, MSA specific features such as elevation could explain a considerable portion of the observed correlation between residential compactness and temperature of the MSA center, and controlling for them increases the effects, in particular, seasonal coefficients.

4.5 DiD Results

Focusing on the reverse causality bias , Difference-in-Difference estimator is appealing. However, it does not account for the unobserved heterogeneity and requires further investigation. **Table** T-6 shows the DiD estimates for the fixed bound scheme. At first glance, it is noticable that DiD coefficients are all positive (unlike RC coefficients previously). It is due to the definition of DiD and what it grasps. DiD setup here compares in-bound and out-bound averages for the pre and post-intervention periods while taking into account some observed heterogeneities. Intervention here is development of U.S. federal high ways, which stimulates sprawling. Since sprawl and residential compactness moving in opposite directions, positive DiD coefficient is expected. Also, note that coefficients for winter and fall are closer to zero but not negative. It mirrors their behavior in the previous section when RC coefficients were more positive for colder seasons. Annual MSA temperature is positively and statistically significantly affected by the growth in sprawl or reduction in residential compactness. Comparing DiD with fixed effect estimates, it is likely that different biases are not completely opposing each other, and their combination may exacerbate the effects. Unconditional average effects are shown for interaction of control/treated and pre/post groups in **Figure** G-13 and **Figure** G-14 that respectively show the results for fixed and flexible schemes. As apparent, while average of the control treated distribution moves to the right after intervention, for control group this movement is slightly to the left and hence overall DiD is positive. Also noticeable is the bi-modal distribution of each group that suggests non-linearity in the effects and possible improvement in DiD precision if two different DiD are calculated for warmer and colder MSAs. The flexible bound scheme increases the unconditional DiD effect but is really close in the shape of the distribution.

4.6 Instrumental Variable

Having a panel data, Instrumental Variable (IV) method can in theory address both reverse causality endogeneity and endogeneity caused by the unobserved fixed heterogeneity. Borrowing the predicted values of highways from Baum-Snow (2007) and, using it as an instrument for the constructed RC (changes in the opposite direction of sprawl), I can address the reverse causality problem. Furthermore, having longitudinal data by construct, I can control for the MSAs fixed effects and address the endogeneity issue due to the unobserved heterogeneity. As a result, this analysis is less likely to suffer from various sources of the endogeneity, and the estimation results are more likely to reflect the causal effects of sprawl on the heat island effect. However, if utilized instrument affects outcome directly, or in presence of weak instrument with low correlation with endogenous variable (residential compactness), the results are not reliable and may suffer from grasping spurious relationships and reflecting overall data trends as causal relationship.

Table T-8 shows the effect of residential compactness on the heat island effect using the instrumental variable of planned highways, and MSA fixed effect using fixed bounds. Estimation includes all the observations for all four waves and 20 years (1972-2004). The IV estimates should be compared with both fixed effect estimates and DiD, as IV incorporates advantages of both methods. IV effects are much larger than fixed effect calculated estimates. Since, comparing with the fixed effect method, IV reduces the reverse causality problem, increase in effects suggests two endogeneities are complement and working in the same direction. Namely, since after controlling for endogeneity effects are increasing, the nature of the reverse causality and unobserved heterogeneity is to reduce the observed effects and hence correlations do not show severity of the effect. **Table** T-9 showing the same result for the flexible bound scheme. The results in this scheme are following the results from fixed scheme closely, meaning flexible bounds do not deviate much from the fixed bounds.

4.7 Orthogonality of IV and Control group

Results from previous section and IV estimates were based on the assumption that, given the instrument is valid to construct exogenous variation in residential compactness (opposite of the scatteredness or sprawl), instrument does not affect outcome directly (temperature). However, developing highways, even for places where it does not stimulate residential relocation, may increase temperature by conducting traffic and industrial activities through surrounding areas of MSA and, consequently, affects temperature of not only MSA center, but surrounding areas as well. IV method in this case, overestimates the effect of sprawl on the UHI as it combines the effect of industrial and other activities associated with the development of highways, with the effect from sprawling. To verify that if this is a problem in IV estimation from previous section or not, I estimate IV coefficients for the temperature of the out-bound areas. If IV estimates for out-bound are significant, then it means the IV estimates of the in-bounds were not pure causal effects and should be adjusted.

This results are shown in **Table** T-10 for the fixed scheme and in **Table** T-11 for the flexible scheme. these IV estimates indicate the control groups (out-bound areas) are affected by the exogenous changes in residential compactness in both schemes. In another words, instrument affects the outcome directly. Comparing these estimates with the IV estimates of the in-bounds, it is obvious that IV estimates of the control group (**Tables** T-10 and T-11) are much smaller than those for treated group (**Tables** T-8 and T-9), and as a result IV estimates are potentially capable to address pure causal effect if being de-trended by control estimates. I approach this problem by incorporating hybrid estimates, meaning estimating IV with fixed effects on the panel data where outcome is the difference between treated and control group. This approach combines DiD and IV estimates and is capable of increasing identification power of the IV, by making sure IV is orthogonal to the overall trends in the data.

4.8 Hybrid Model

Hybrid model as explained in the previous section produces effects which are immune to the non-orthogonality issue while inherits the benefits of the IV estimates completely. **Table** T-12 shows the hybrid estimates for the fixed scheme. It reduces the effects comparing to the IV estimates and produces negative effects for all seasons, however, coefficients are less significant and for winter the coefficient is not significant in 10 %. **Table** T-13 reflects the confusion over the control group definition in flexible scheme as the geographical area associated with the control group moves in this scheme and hence, coefficients are less significant than those from fixed scheme, however, they are all still negative.

4.9 Comparison of the Results

It is possible to compare the results between IV and hybrid methods as both of them are calculating the marginal effect of the predicted residential compactness. However, this is not straightforward when the goal is to include DiD into comparison as well. Note that DiD coefficient reports the effect of a change based on some intervention and not necessarily one unit change in our measure of residential compactness. Interestingly DiD shows positive coefficient while IV and hybrid coefficients are negative. It means that due to the intervention RC level is decreased by time, which is what one expects by development of federal highways. To be able to compare DiD, with IV and hybrid coefficient, I project the predicted residential compactness for each MSA and then multiply the decrements in RCs by the estimated coefficients for each of the IV and hybrid methods. This allows me to calculate the MSA-specific effect that each of the IV and hybrid methods are suggesting. Average of the distribution of such MSA-specific effect can be compared with DiD.

The results are shown in **Figure** G-15 and **Figure** G-16 which respectively associated with fixed and flexible schemes. As shown in these figures, DiD suggests the largest effects. However, since DiD does not take into account the endogeneity from the unobserved heterogeneity, it is still a biased estimate of the causal effect. The difference between DiD and hybrid effect is the biasness due to unobserved heterogeneity endogeneity. IV estimate lies between DiD and hybrid. Again the difference between hybrid and IV reflects the biased from not tacking into account the overall trends in the whole MSA and its surrounding areas.

5 Conclusion

The effect of sprawl on the heat island effect is an empirical question without a clear answer. The range of issues can be from the lack of a precise definition for sprawl to the endogeneity and defining city horizon. This study adopts the procedure developed by Burchfield et al.

(2006) to construct a new measure of sprawl.

Comprehensive and covering measure of sprawl in this study allows for the incorporation of more MSAs and increases the statistical power of the tests. Also, utilizing the information collected by the stations on the surface allows for detailed, daily aggregated surface data, such as the average of the day temperature, maximum and minimum of the daily temperature, dew point, and wind speed. While the focus of this study is temperature, aggregation of these variables allows for a complete, multidimensional analysis of the urban sprawling problem and allows for future studies of the subject.

This study approaches different methods to address the reverse causality problem and provides an overview of the methods and their benefits as well as their deficiencies. Lastly, it suggests a combination of Difference-in-Difference and Instrumental Variable approach to address the endogeneity caused by the reverse causality problem. Also, to better tracking of the problem, I construct a flexible bound scheme that can be used in other studies where the entity under observation changes size through time, such as cities, natural currents, and resources such as woods.

For the first approach in resolving the reverse causality problem, I utilize DiD based on the national program of development of highways. The second method that I employ is the instrumental variable method. I employ an instrument that first developed by Baum-Snow (2007). By testing the orthogonality condition of the instrument, I suggest the combination of the DiD and IV. I show that the scatteredness or sprawl can be responsible for approximately 50 % of the heat island effect. I show that if we do not account for the different types of reverse causality, these endogeneities can obscure the results severely.

Practicing the back of envelope calculation, I look at the explained heat island effect for the MSA that contains Atlanta, as one of the examples of the growth in scatteredness. The Measure of residential compactness in Atlanta changes from -.1540 in 1972 to -.2904 in 2014, which shows $\Delta RC_{Atlanta} = -.1364$. Having a statistically significant estimated coefficient of -10.74 for the residential compactness and dependent variable of annual temperature average using the fixed bound scheme, I calculate the heat island effect that is caused by the increase in scatteredness to be, $E_{\Delta RC|1972-2014} \approx 1.47°F$. This effect is $E_{\Delta RC|1972-2014} \approx 0.91°F$ using flexible bound scheme.

Tables

Table T-1: Summery of GSOD Station Data

Year	Total Stations	Total Station-Days	Average Days per Station
1972	53	19,063	359.68
1973	380	131,430	345.87
1974	381	132,380	347.45
1975	406	135,461	333.65
1976	417	141,561	339.47
1980	448	148,988	332.56
1981	448	147,603	329.47
1982	445	145,624	327.24
1983	452	147,706	326.78
1984	453	149,142	329.23
1990	464	152,433	328.52
1991	448	148,905	332.38
1992	448	147,864	330.05
1993	444	148,687	334.88
1994	434	146,490	337.53
2000	322	113,680	353.04
2001	330	114,075	345.68
2002	339	116,707	344.27
2003	341	118,020	346.1
2004	417	142,249	341.12
2010	942	325,056	345.07
2011	911	320,713	352.05
2012	904	320,319	354.34
2013	881	307,766	349.34
2014	863	306,485	355.14

Number of weather stations, available in the dataset and their changes through the study period.

Table T-2: OLS results of the effects on mean Temperature using fixed bounds

	(1) TEMP(Annual)	(2) TEMP(Winter)	(3) TEMP(Spring)	(4) TEMP(Summer)	(5) TEMP(Autumn)
RC	-12.110***	-16.356***	-10.171***	-8.188***	-16.541***
	(1.91)	(2.72)	(1.64)	(1.48)	(2.12)
Wind Speed	-0.013	-0.059	0.007	0.006	-0.030
	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)
N	1,882	1,887	1,888	1,889	1,888

Standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01.$

Table T-3: OLS results of the effects on mean Temperature using flexible bounds

	(1) Temp(Annual)	(2) Temp(Winter)	(3) Temp(Spring)	(4) Temp(Summer)	(5) Temp(Autumn)
RC	-8.095***	-11.160***	-6.668***	-5.687***	-12.227***
	(1.93)	(2.73)	(1.65)	(1.51)	(2.12)
Wind Speed	-0.021	-0.068*	0.002	0.003	-0.048*
	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)
N	1,807	1,825	1,825	1,826	1,826

Standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01.$

Table T-4: FE OLS results of the effects on mean Temperature using fixed bounds

	(1) TEMP(Annual)	(2) TEMP(Winter)	(3) TEMP(Spring)	(4) TEMP(Summer)	(5) TEMP(Autumn)
RC	-6.962***	6.748***	-17.126***	-9.094***	-5.183**
	(1.77)	(2.29)	(1.37)	(2.14)	(2.22)
Wind Speed	0.029***	0.012	0.026***	0.012	0.023*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	1,882	1,887	1,888	1,889	1,888

Standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01.$

Table T-5: FE OLS results of the effects on mean Temperature using flexible bounds

	(1) Temp(Annual)	(2) Temp(Winter)	(3) Temp(Spring)	(4) Temp(Summer)	(5) Temp(Autumn)
RC	-5.232***	7.035***	-14.991***	-7.818***	-4.694**
	(1.79)	(2.26)	(1.37)	(2.14)	(2.24)
Wind Speed	0.033***	0.014	0.023***	0.028**	0.021
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	1,807	1,825	1,825	1,826	1,826

Standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$.

Table T-6: Diff-in-Diff effects on mean Temperature using fixed bounds

	(1) TEMP(Annual)	(2) TEMP(Winter)	(3) TEMP(Spring)	(4) TEMP(Summer)	(5) TEMP(Autumn)
DiD	0.592**	0.115	0.522*	0.592**	0.122
	(0.27)	(0.35)	(0.29)	(0.27)	(0.38)
Treatment	0.032	-0.012	0.179	0.038	0.117
	(0.20)	(0.25)	(0.21)	(0.19)	(0.28)
Post	0.053	-1.011***	0.763***	0.330*	0.675**
	(0.20)	(0.25)	(0.21)	(0.19)	(0.27)
Latitude	-1.533***	-2.234***	-1.338***	-0.931***	-1.673***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Wind Speed	-0.052**	-0.073**	-0.031	0.032	-0.025
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
N	1,579	1,575	1,577	1,579	1,579

Standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$.
Causal effect of changes in residential distribution and urban development on the Temperature of MSA's center. Difference in Difference method is based on Wave 1 (1972-1976) as pre-intervetion period and Wave 4 (2000-2004) as post-intervention. Control group is constructed to be the surrounding area, fixed in time. DiD coefficient reflects the causal effect and is statistically significant for Annual temperature, showing due to changes in sprawl patterns (horizontal development of cities) temperature of MSA's center is raised by 0.625 degree Farenheit. It also shows most of the effect is through the changes in temperature during Spring and Summer time.

Table T-7: Diff-in-Diff effects on mean Temperature using flexible bounds

	(1) Temp(Annual)	(2) Temp(Winter)	(3) Temp(Spring)	(4) Temp(Summer)	(5) Temp(Autumn)
DiD	0.561**	0.066	0.504*	0.596**	0.129
	(0.28)	(0.36)	(0.29)	(0.27)	(0.39)
Treatment	0.035	-0.014	0.183	0.039	0.117
	(0.20)	(0.26)	(0.21)	(0.20)	(0.28)
Post	0.058	-0.986***	0.756***	0.303	0.676**
	(0.20)	(0.26)	(0.21)	(0.20)	(0.28)
Latitude	-1.532***	-2.234***	-1.338***	-0.935***	-1.670***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Wind Speed	-0.046**	-0.076***	-0.026	0.034	-0.027
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
N	1,563	1,561	1,561	1,563	1,563

Standard errors in parentheses

$*p < 0.1, **p < 0.05, ***p < 0.01$.

Causal effect of changes in residential distribution and urban development on the Temperature of MSA's center. Difference in Difference method is based on Wave 1 (1972-1976) as pre-intervetion period and Wave 4 (2000-2004) as post-intervention. Control group is constructed to be the surrounding area that varies depending on changes in residential distribution to reflect changes in city boundaries. DiD coefficient reflects the causal effect and is statistically significant for Annual temperature, showing due to changes in sprawl patterns (horizontal development of cities) temperature of MSA's center is raised by 0.579 degree Farenheit. Results are driven mostly by changes in termperature in warmer seasons of summer and spring.

Table T-8: IV effects on mean Temperature using fixed bounds

	(1) TEMP(Annual)	(2) TEMP(Winter)	(3) TEMP(Spring)	(4) TEMP(Summer)	(5) TEMP(Autumn)
RC	-14.348***	14.366**	-29.599***	-21.715***	-24.271***
	(4.53)	(5.83)	(3.55)	(5.49)	(5.77)
Wind Speed	0.027***	0.014	0.022***	0.008	0.017
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	1,882	1,887	1,888	1,889	1,888

Standard errors in parentheses

$*p < 0.1, **p < 0.05, ***p < 0.01$.

IV estimation on the Heat Island Effects for Waves 1 through 4 (1972-2002), using fixed Bound Scheme is shown. RC (residential compactness) coefficient shows the statistically significant causal relationship. Employed instrument is the planned portion of highways. As development of highways motivates individuals to relocate to the new suburbs and surrounding areas of the MSA center, scatteredness increases and residential compactness decreases. Hence, negative coefficient of RC is in accordance with the Urban Heat Island effect hypothesis which predicts, developing horizontal constructions increases the temperature of the central parts in cities. As residential compactness decreases, temperature of the MSA center increases. IV estimates of the causal relationships are significant for all seasons of year. However, for winter this relationship is positive and for autumn it is less significant than spring and summer. Thus, IV estimates reflect what was produced by DiD estimates and further, shows more extreme weather should be expected for the MSA centers during winter and summer, as cities develop horizontally.

Table T-9: IV effects on mean Temperature using flexible bounds

	(1) Temp(Annual)	(2) Temp(Winter)	(3) Temp(Spring)	(4) Temp(Summer)	(5) Temp(Autumn)
RC	-13.341***	14.718**	-26.234***	-22.992***	-23.388***
	(4.54)	(5.72)	(3.51)	(5.49)	(5.77)
Wind Speed	0.028***	0.018	0.017**	0.021	0.011
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	1,807	1,825	1,825	1,826	1,826

Standard errors in parentheses

$*p < 0.1, **p < 0.05, ***p < 0.01$.

IV estimation on the Heat Island Effects for Waves 1 through 4 (1972-2002), using flexible Bound Scheme is shown. RC (residential compactness) coefficient shows the statistically significant causal relationship. Employed instrument is the planned portion of highways. As development of highways motivates individuals to relocate to the new suburbs and surrounding areas of the MSA center, scatteredness increases and residential compactness decreases. Hence, negative coefficient of RC is in accordance with the Urban Heat Island effect hypothesis which predicts, developing horizontal constructions increases the temperature of the central parts in cities. As residential compactness decreases, temperature of the MSA center increases. These IV estimates of the causal relationships are significant for most of the seasons. They are closer to DiD effects comparing with the IV estimates with fixed bounds. Like fixed bound scheme, they show positive coefficient for winter but statistically insignificant.

Table T-10: Analysis of the sensitivity of Control group to the Instrument (fixed bounds)

	(1) TEMP(Annual)	(2) TEMP(Winter)	(3) TEMP(Spring)	(4) TEMP(Summer)	(5) TEMP(Autumn)
RC	-5.840**	12.774***	-23.114***	-12.460***	-13.892***
	(2.58)	(4.01)	(3.12)	(2.78)	(3.45)
Wind Speed	0.005	0.000	-0.008	-0.001	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	2,136	2,134	2,135	2,135	2,135

Standard errors in parentheses

$*p < 0.1, **\,p < 0.05, ***p < 0.01$.

IV estimation on the Heat Island Effects for Waves 1 through 4 (1972-2002), using fixed Bound Scheme is shown. RC (residential compactness) coefficient shows the statistically significant causal relationship. Employed instrument is the planned portion of highways. As development of highways motivates individuals to relocate to the new suburbs and surrounding areas of the MSA center, scatteredness increases and residential compactness decreases. Hence, negative coefficient of RC is in accordance with the Urban Heat Island effect hypothesis which predicts, developing horizontal constructions increases the temperature of the central parts in cities. As residential compactness decreases, temperature of the MSA center increases. IV estimates of the causal relationships are significant for all seasons of year. However, for winter this relationship is positive and for autumn it is less significant than spring and summer. Thus, IV estimates reflect what was produced by DiD estimates and further, shows more extreme weather should be expected for the MSA centers during winter and summer, as cities develop horizontally.

Table T-11: Analysis of the sensitivity of Control group to the Instrument (flexible bounds)

	(1) Temp(Annual)	(2) Temp(Winter)	(3) Temp(Spring)	(4) Temp(Summer)	(5) Temp(Autumn)
RC	-7.985***	10.509***	-17.532***	-7.888***	-15.577***
	(2.50)	(3.87)	(2.72)	(2.67)	(3.43)
Wind Speed	-0.017**	-0.025**	-0.009	-0.011	-0.027**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	2,040	2,039	2,039	2,040	2,040

Standard errors in parentheses

$*p < 0.1, **p < 0.05, ***p < 0.01$.

IV estimation on the Heat Island Effects for Waves 1 through 4 (1972-2002), using fixed Bound Scheme is shown. RC (residential compactness) coefficient shows the statistically significant causal relationship. Employed instrument is the planned portion of highways. As development of highways motivates individuals to relocate to the new suburbs and surrounding areas of the MSA center, scatteredness increases and residential compactness decreases. Hence, negative coefficient of RC is in accordance with the Urban Heat Island effect hypothesis which predicts, developing horizontal constructions increases the temperature of the central parts in cities. As residential compactness decreases, temperature of the MSA center increases. IV estimates of the causal relationships are significant for all seasons of year. However, for winter this relationship is positive and for autumn it is less significant than spring and summer. Thus, IV estimates reflect what was produced by DiD estimates and further, shows more extreme weather should be expected for the MSA centers during winter and summer, as cities develop horizontally.

Table T-12: Hybrid method effects on mean Temperature using fixed bounds

	(1) TEMP(Autumn)
RC	-24.271***
	(5.77)
Wind Speed	0.017
	(0.01)
N	1,888

Standard errors in parentheses

$*p < 0.1, **p < 0.05, ***p < 0.01$.

IV estimation on the Heat Island Effects for Waves 1 through 4 (1972-2002), using fixed Bound Scheme is shown. RC (residential compactness) coefficient shows the statistically significant causal relationship. Employed instrument is the planned portion of highways. As development of highways motivates individuals to relocate to the new suburbs and surrounding areas of the MSA center, scatteredness increases and residential compactness decreases. Hence, negative coefficient of RC is in accordance with the Urban Heat Island effect hypothesis which predicts, developing horizontal constructions increases the temperature of the central parts in cities. As residential compactness decreases, temperature of the MSA center increases. IV estimates of the causal relationships are significant for all seasons of year. However, for winter this relationship is positive and for autumn it is less significant than spring and summer. Thus, IV estimates reflect what was produced by DiD estimates and further, shows more extreme weather should be expected for the MSA centers during winter and summer, as cities develop horizontally.

Table T-13: Hybrid method effects on mean Temperature using flexible bounds

	(1) Temp(Annual)	(2) Temp(Winter)	(3) Temp(Spring)	(4) Temp(Summer)	(5) Temp(Autumn)
RC	-6.695	-0.837	-9.779***	-16.348***	-5.810
	(4.80)	(3.22)	(3.02)	(5.30)	(4.56)
Wind Speed	0.049***	0.046***	0.030***	0.034***	0.036***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	1,807	1,824	1,824	1,826	1,826

Standard errors in parentheses

$*p < 0.1, **p < 0.05, ***p < 0.01$.

IV estimation on the Heat Island Effects for Waves 1 through 4 (1972-2002), using fixed Bound Scheme is shown. RC (residential compactness) coefficient shows the statistically significant causal relationship. Employed instrument is the planned portion of highways. As development of highways motivates individuals to relocate to the new suburbs and surrounding areas of the MSA center, scatteredness increases and residential compactness decreases. Hence, negative coefficient of RC is in accordance with the Urban Heat Island effect hypothesis which predicts, developing horizontal constructions increases the temperature of the central parts in cities. As residential compactness decreases, temperature of the MSA center increases. IV estimates of the causal relationships are significant for all seasons of year. However, for winter this relationship is positive and for autumn it is less significant than spring and summer. Thus, IV estimates reflect what was produced by DiD estimates and further, shows more extreme weather should be expected for the MSA centers during winter and summer, as cities develop horizontally.

Graphs

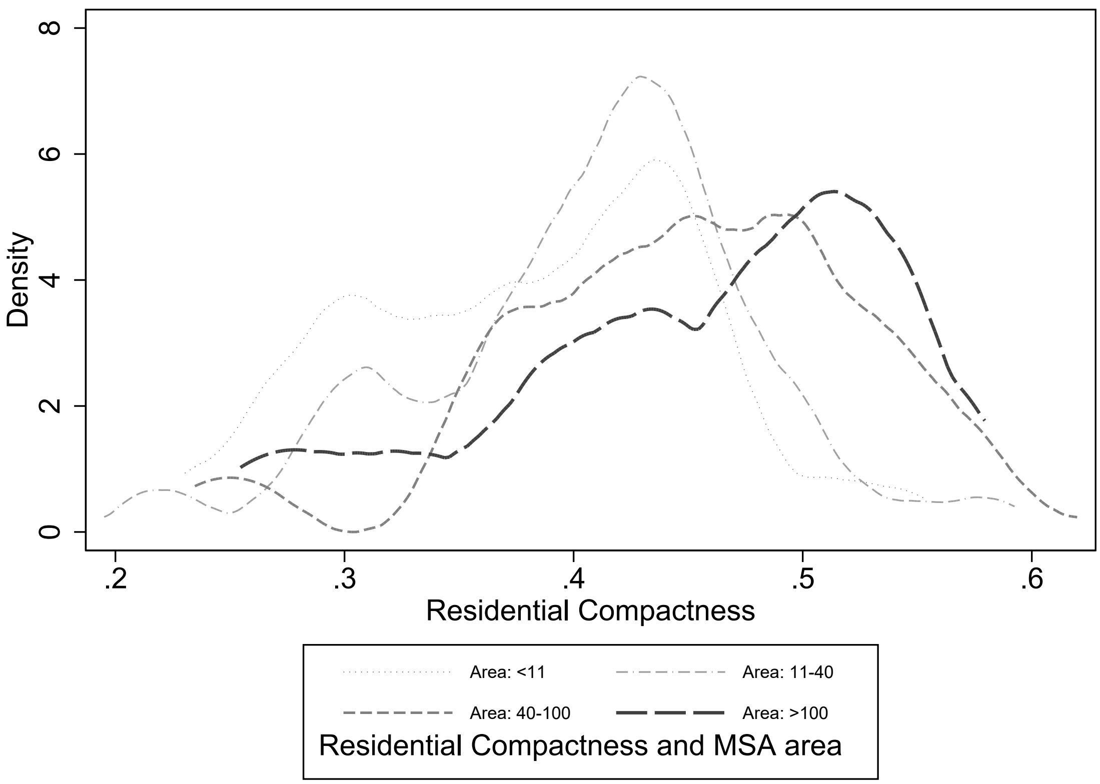

Figure G-1: Distribution of Residential Compactness by 1950 Area of MSA

Distribution of the adjusted measure of Residential Compactness is depicted for each MSA's area category as set in 1950. While we might expect to observe negative correlation between area and Residential compactness, positive correlation is apparent. It suggests, development of large MSAs has been happened before 1950 and by the time, large MSAs also represented highly dense area, as is reflected in Residential compactness.

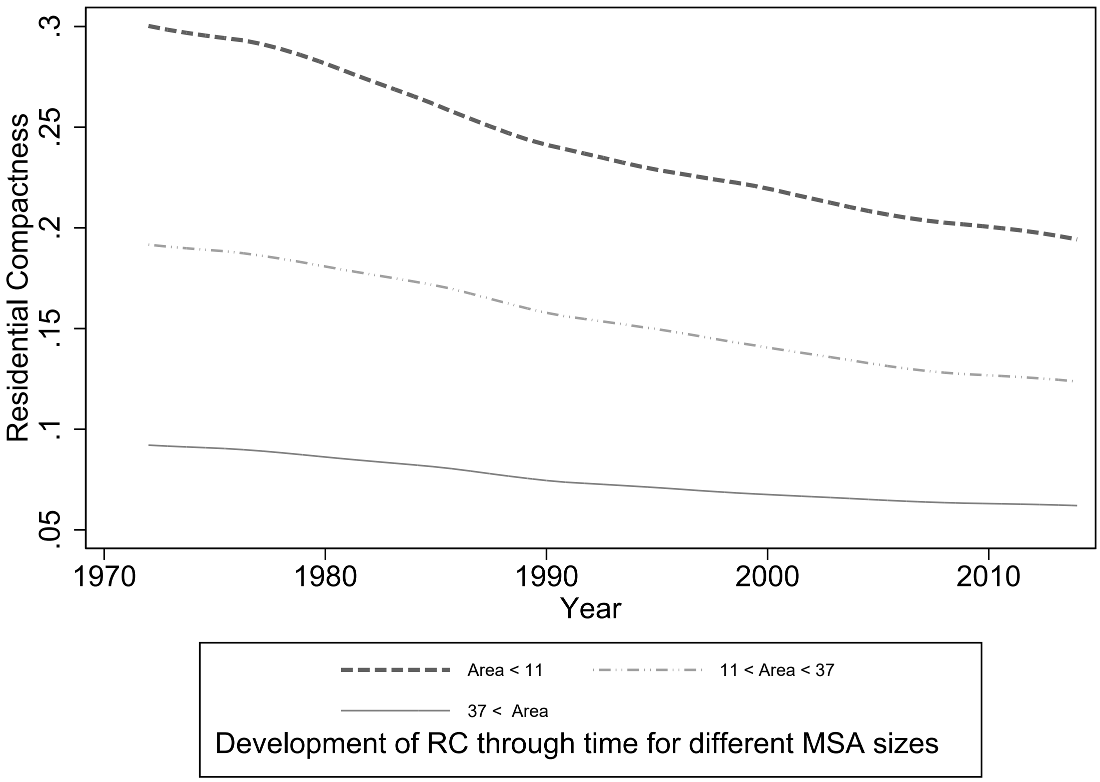

Figure G-2: Changes in the Residential Compactness in time for different MSA sizes (Fixed bounds)

Evolution of Residential Compactness in time for three categories of MSA sizes. Three categories are depicted associated with 25 and 75 percentiles. Smallest category shows the fastest increase in scatteredness (reduction in residential compactness) comparing to the other two categories.

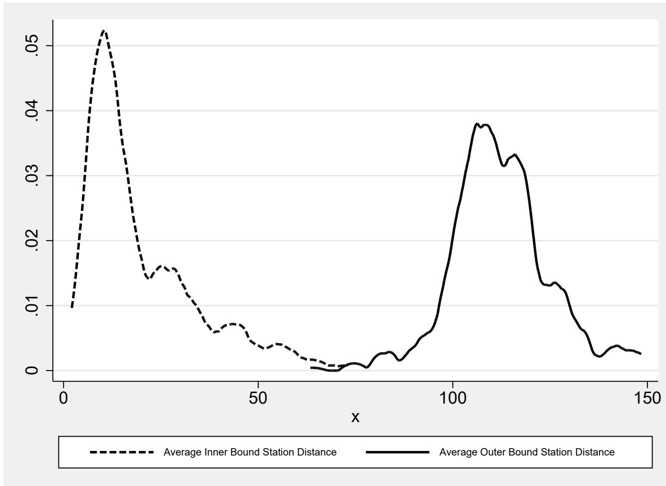

Figure G-3: Average distance to Center (Static Bound Scheme)

Source: Author's Calculation using GSOD and ArcGIS

Distribution of the average distance from stations inside the bound (Inner bound) and stations outside the bound (Outer bound) to the center, for all the MSA-years, with static bound scheme. Dashed line shows the average distance distribution for stations inside the bound and solid line is for stations outside of bound.

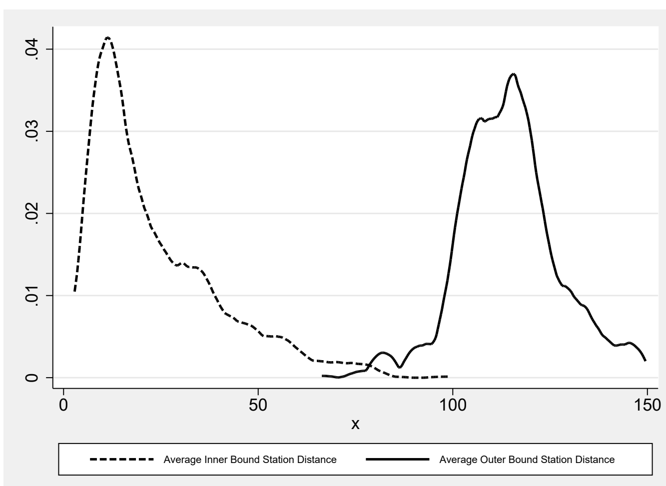

Figure G-4: Average distance to Center (Dynamic Bound Scheme)

Source: Author's Calculation using GSOD and ArcGIS

Distribution of the average distance from stations inside the bound (Inner bound) and stations outside the bound (Outer bound) to the center, for all the MSA-years, with dynamic bound scheme. Dashed line shows the average distance distribution for stations inside the bound and solid line is for stations outside of bound.

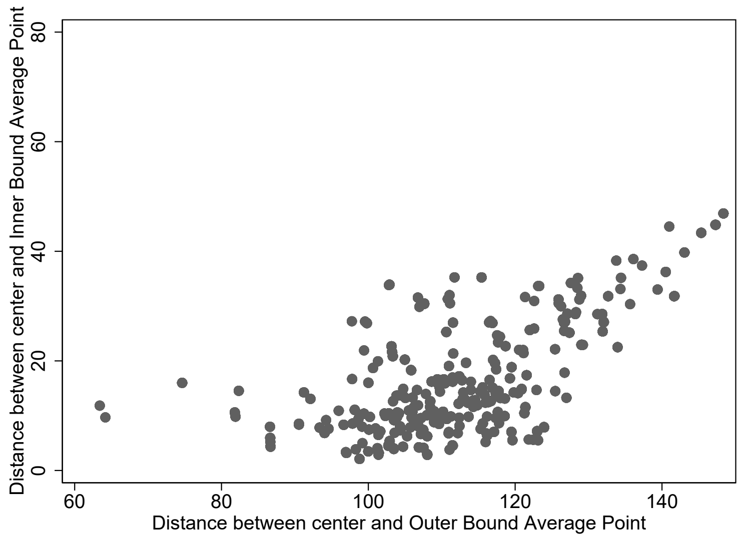

Figure G-5: Average distance to Center Scatter Plot (Static Bound Scheme).
Source: Author's Calculation using GSOD and ArcGIS
The negative correlation between average distance of Outside and Inside stations caused by the static bound scheme.

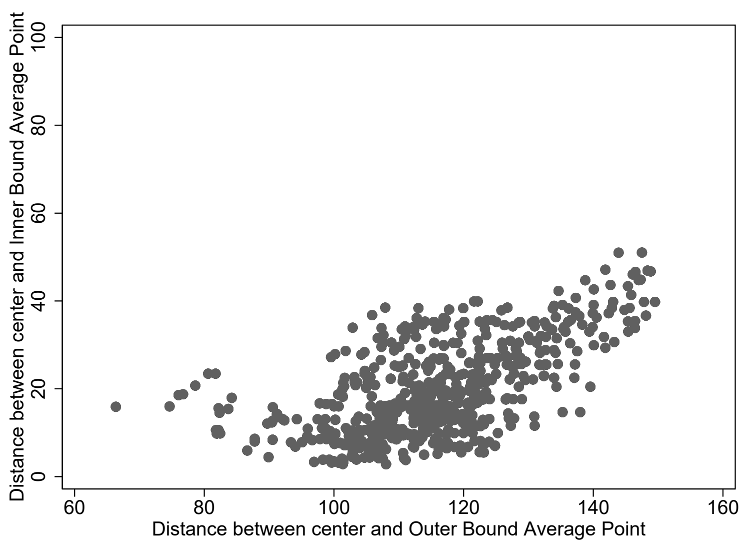

Figure G-6: Average distance to Center Scatter Plot(Dynamic Bound Scheme).
Source: Author's Calculation using GSOD and ArcGIS
The negative correlation between average distance of Outside and Inside stations caused by the dynamic bound scheme.

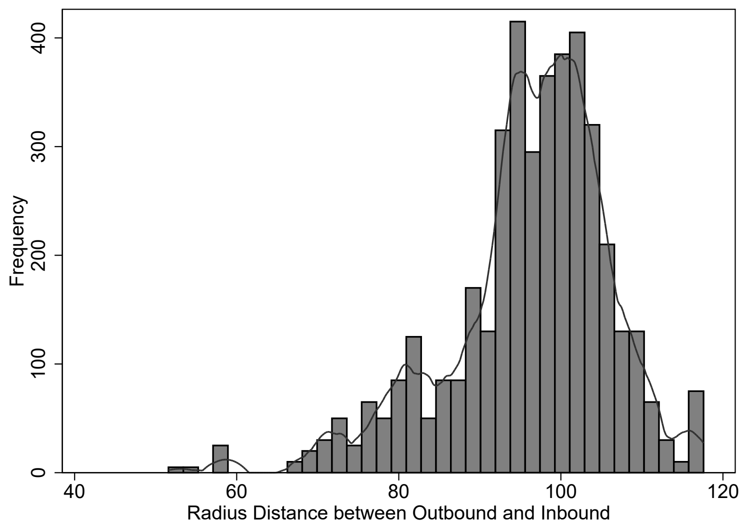

Figure G-7: Distance Between Stations (Static Bound Scheme)
Source: Author's Calculation using GSOD and ArcGIS
Distribution of Radius distance between Out and Inbound stations in the static bound scheme.

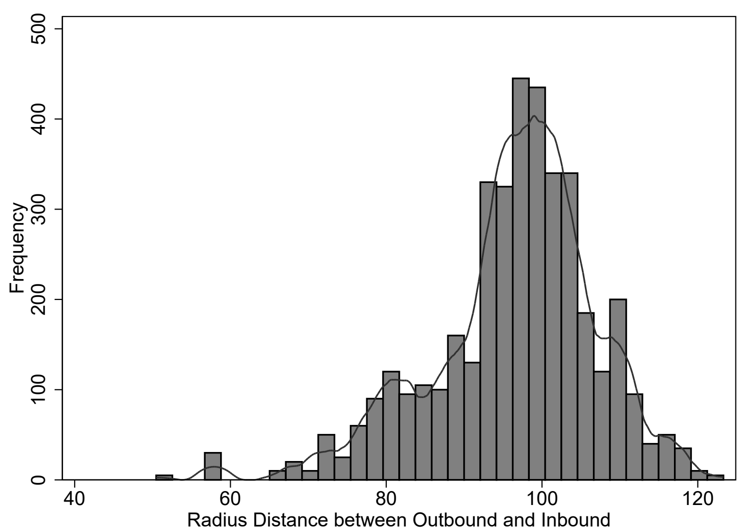

Figure G-8: Distance Between Stations (Dynamic Bound Scheme)
Source: Author's Calculation using GSOD and ArcGIS
Distribution of Radius distance between Out and Inbound stations in the dynamic bound scheme.

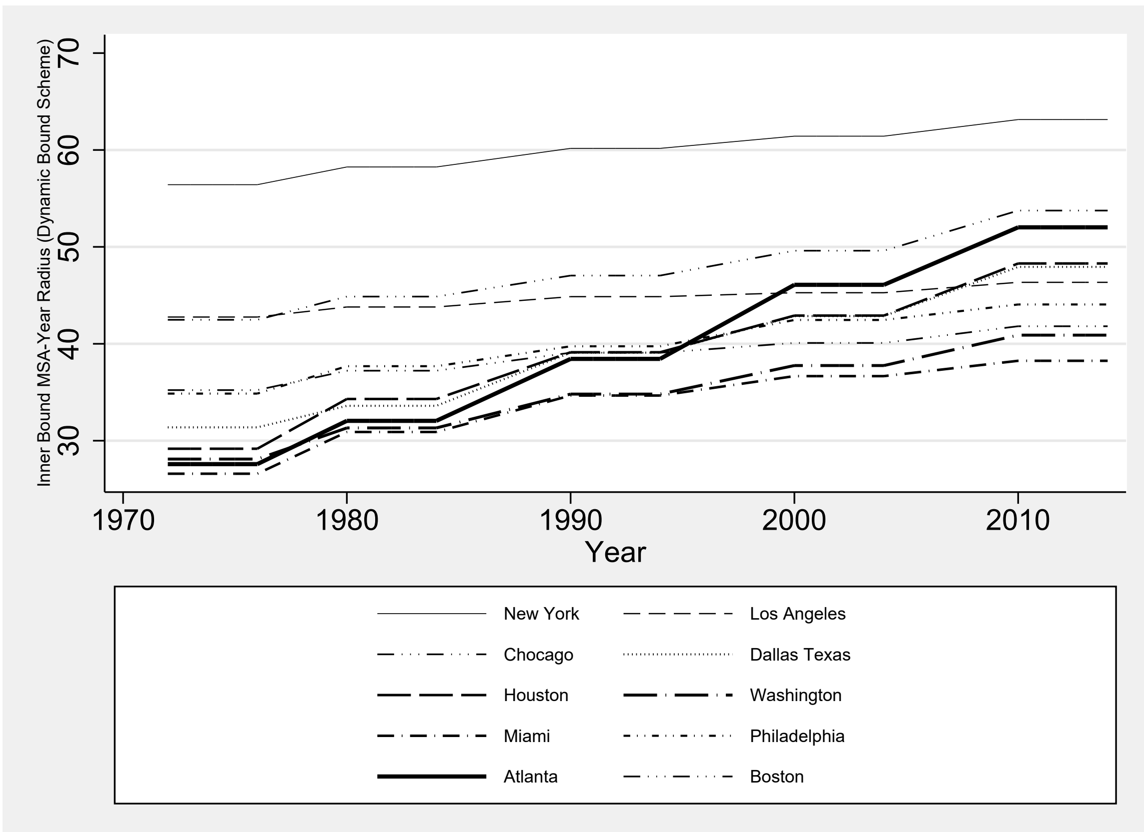

Figure G-9:

Source: Author's Calculation using GSOD and ArcGIS

Time series of the inner radius of the ten MSAs, associated to the big cities in U.S. from 1972 to 2014. Atlanta shows biggest rise in the inner radius, that reflects the fact of rapid rate of change of the lands usage to residential use and grow in the city limits.

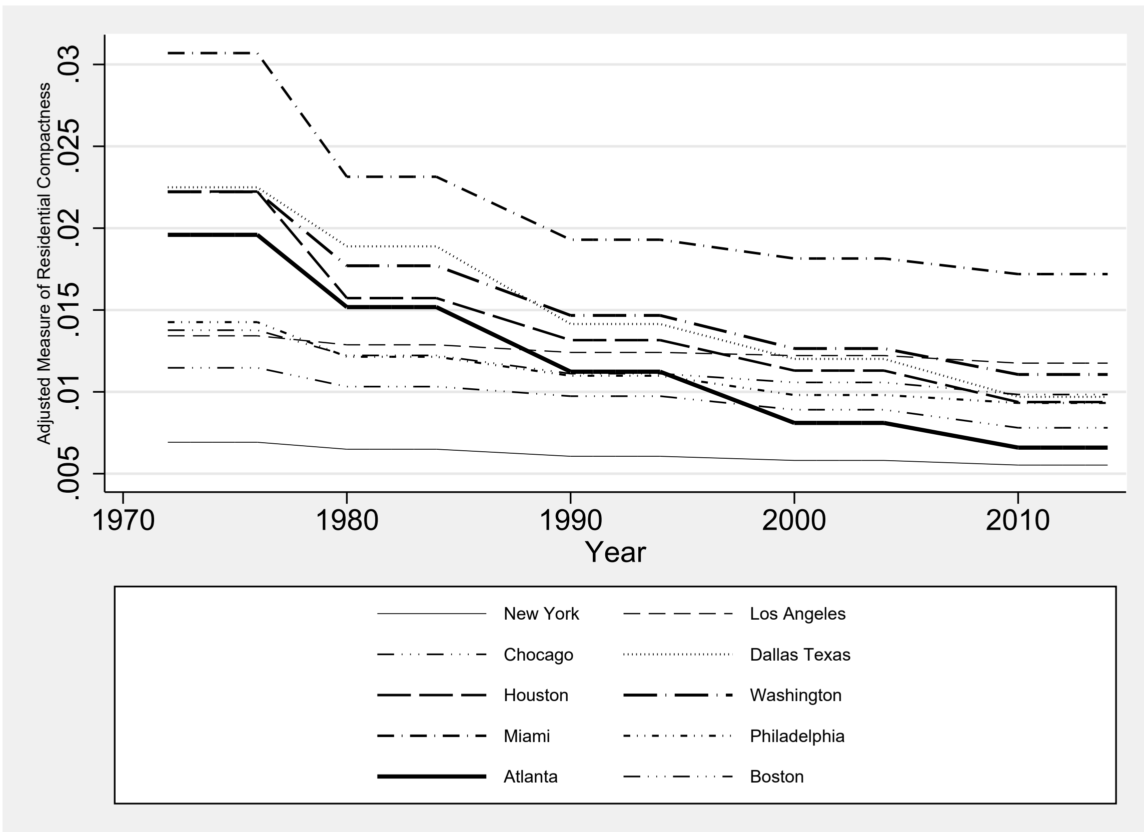

Figure G-10: Residential Compactness for selected cities (Flexible bounds)

Source: Author's Calculation using GSOD and ArcGIS

Changes in the measure of residential compactness for sample of MSAs for the ten cities. Atlanta experiences biggest drop in the residential compactness. It means that sprawl/scatteredness rate was increased in Atlanta MSA more than any other MSA in this sample of MSAs.

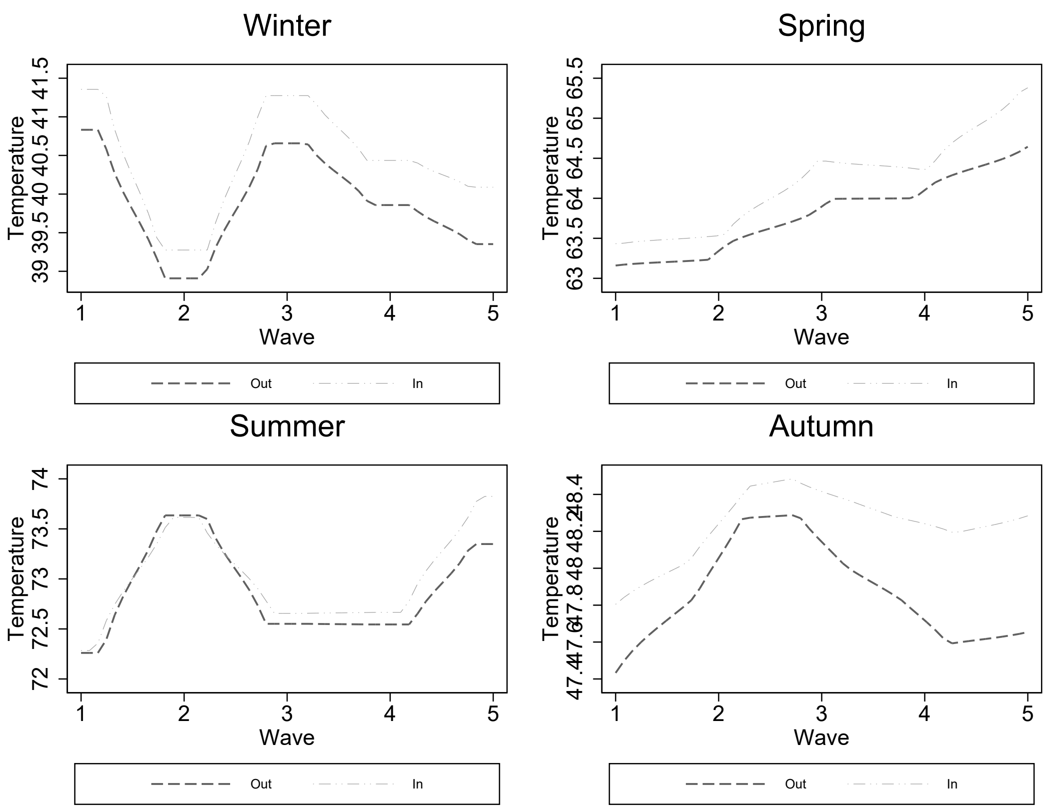

Figure G-11: Movements of the temperature in time (Fixed bounds)

Seasonal average of the daily mean temperature is shown for in and out of the bound. Temperature of the inner areas are on average higher than out of bound areas. The irregularities are due to the fixed bound scheme that does not allow for change in bounds and hence, MSAs which are developing horizontally add to the outer bound temperature and move the overall averages.

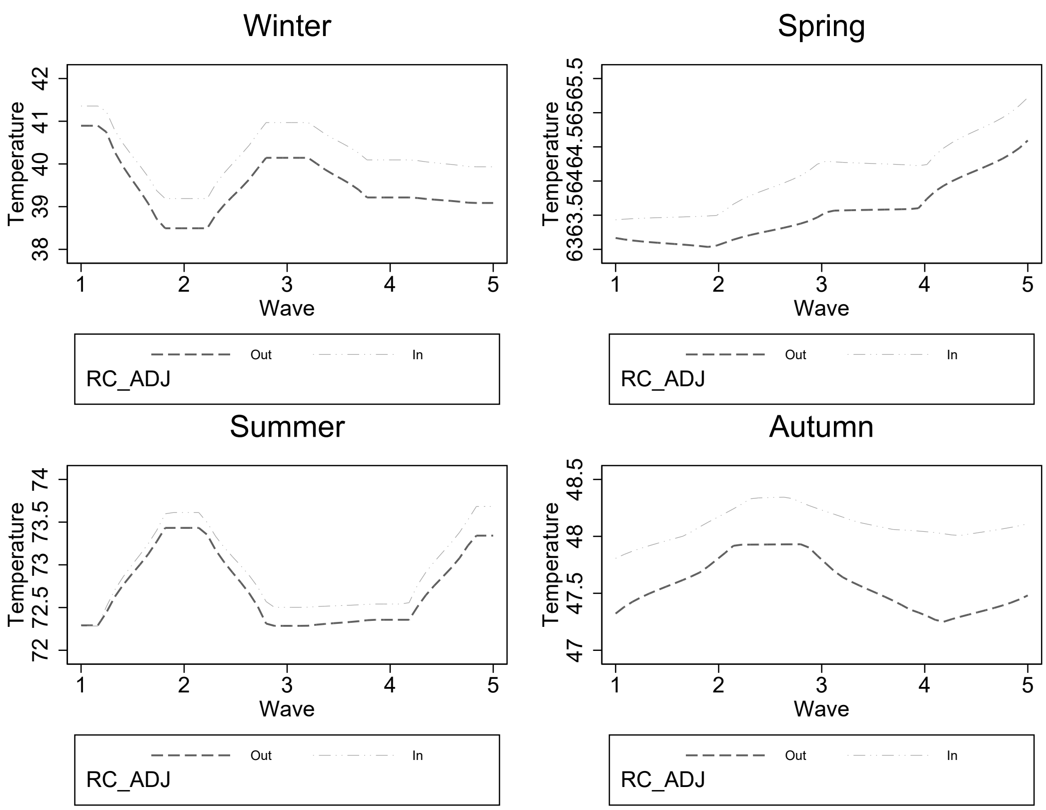

Figure G-12: Movements of the temperature in time (Flexible bounds)

Seasonal average of the daily mean temperature is shown for in and out of the bound. Temperature of the inner areas are on average higher than out of bound areas. Since, flexible scheme is used, the results are more consistent with the expectation and temperatures in and out of the bounds are consistently diverged.

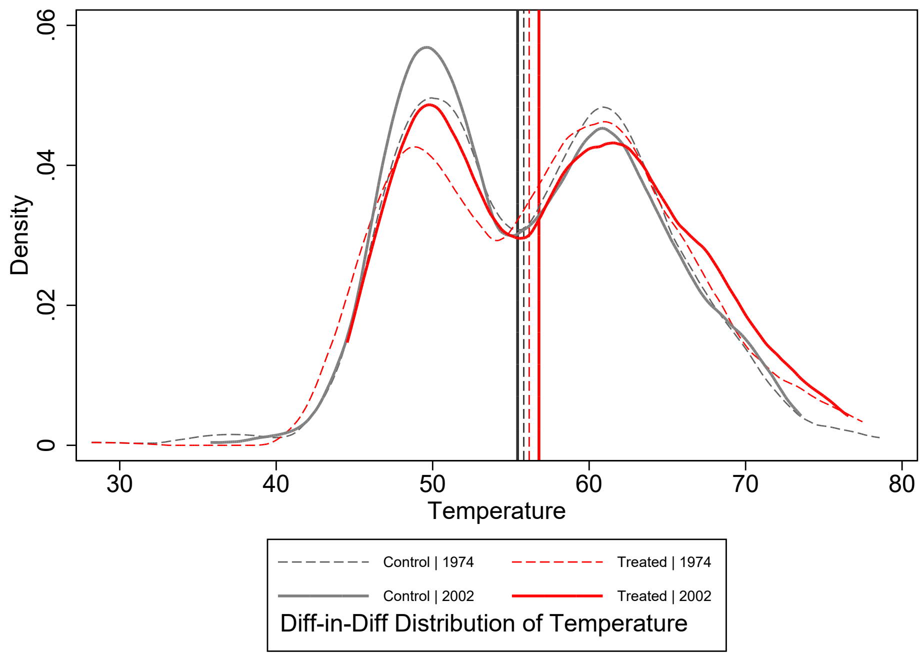

Figure G-13: Distributional effect of Treatment and Time (Fixed bounds)

Unconditional distributions of Treatment and Time dimension are presented. Time moves the average of the treatment group to the right, while control group moves to the left as time passes by.

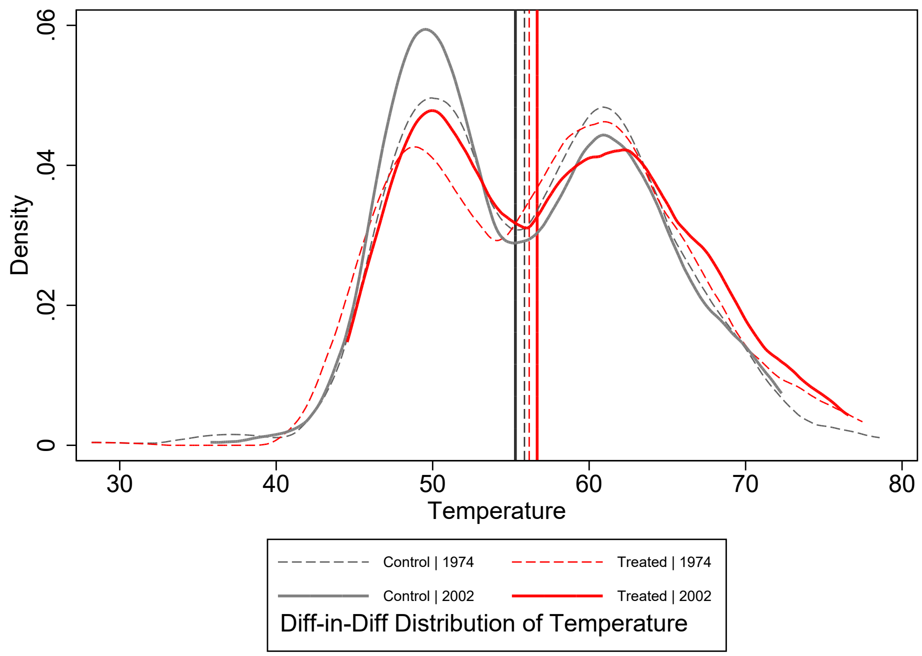

Figure G-14: Distributional effect of Treatment and Time (Flexible bounds)
Unconditional distributions of Treatment and Time dimension are presented. Like fixed bounds, the effect of treatment is exacerbated by time.

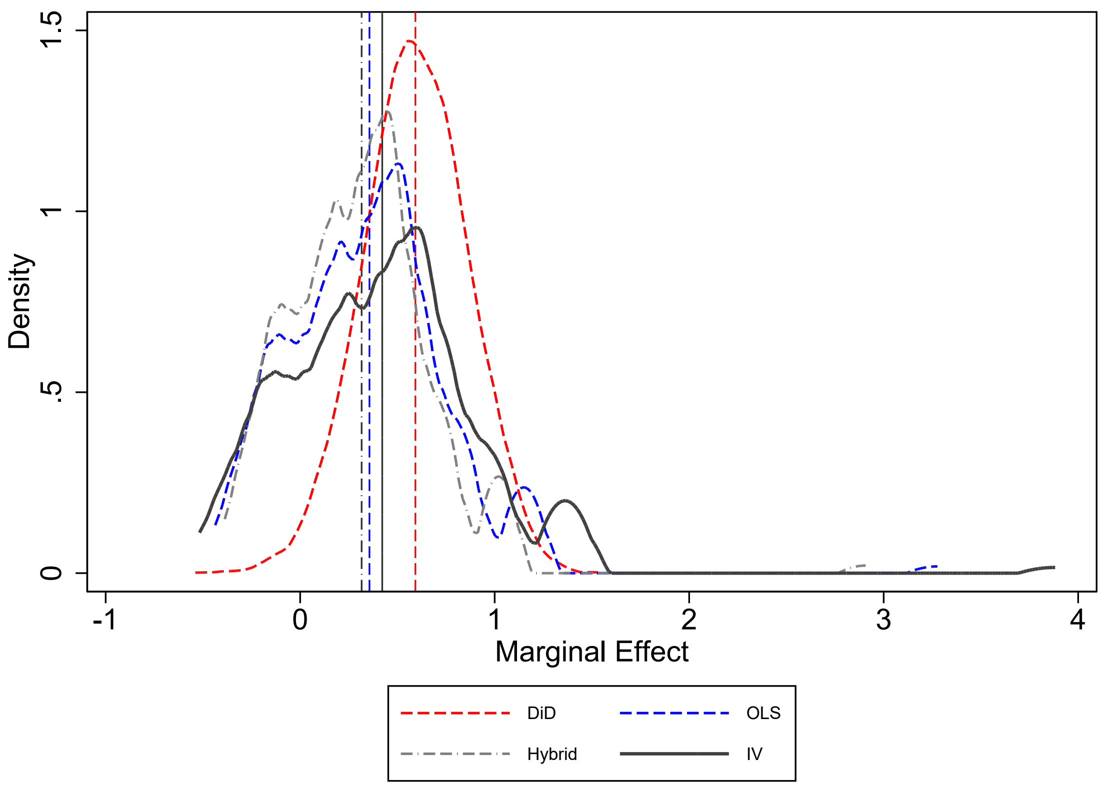

Figure G-15: Distribution of Marginal effects for each utilized method (fixed bounds)
Results from IV and hybrid methods are compared against DiD marginal effects. for each method, predicted residential compactness is calculated. Each distribution is the projected contribution of RC onto Temperature. Hybrid method produces closer ME to DiD than IV. It is due to the fact, that IV affects control groups as well as treated group. However, it affects treatment group twice as severely as control group and hence has explanation power. Hybrid model helps to reduce the spurious relationship between IV and annual temperature.

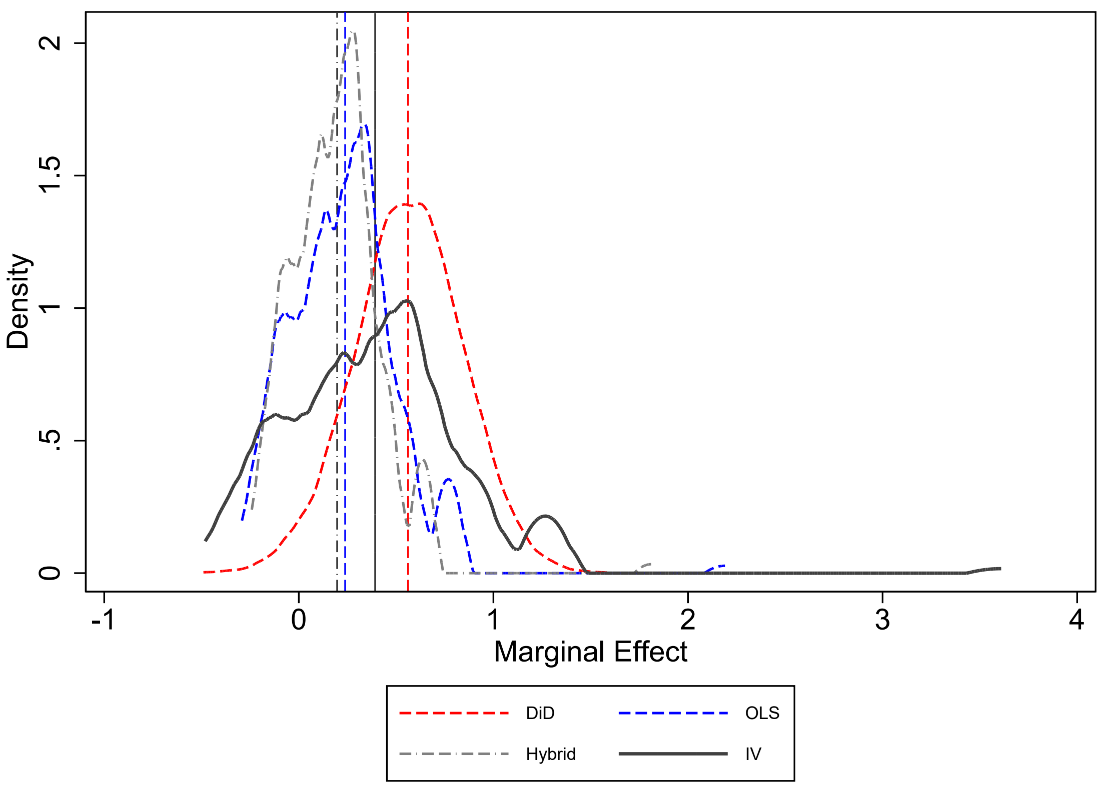

Figure G-16: Distribution of Marginal effects for each utilized method (flexible bounds)
Results from IV and hybrid methods are compared against DiD marginal effects. for each method, predicted residential compactness is calculated. Each distribution is the projected contribution of RC onto Temperature. Hybrid method produces closer ME to DiD than IV. It is due to the fact, that IV affects control groups as well as treated group. However, it affects treatment group twice as severely as control group and hence has explanation power. Hybrid model helps to reduce the spurious relationship between IV and annual temperature.

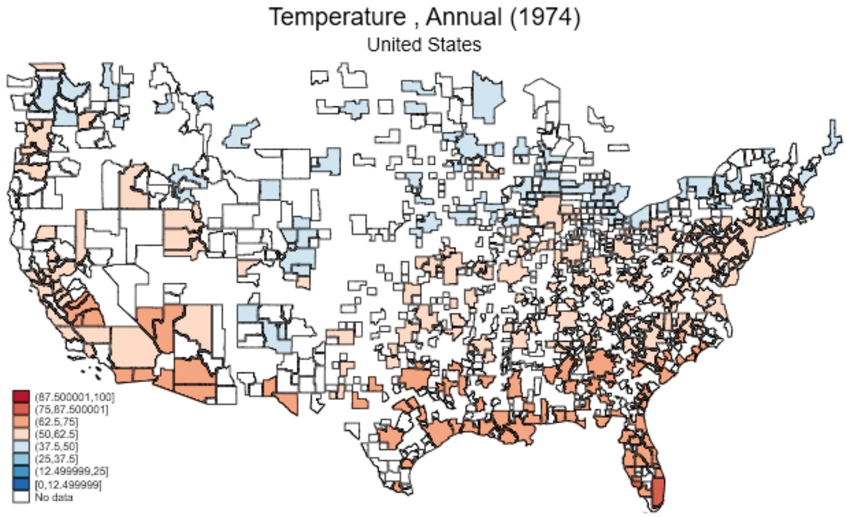

Figure G-17: Temperature Data on the collected MSAs in 1974

Source: Author's Calculation using ArcGIS and GSOD

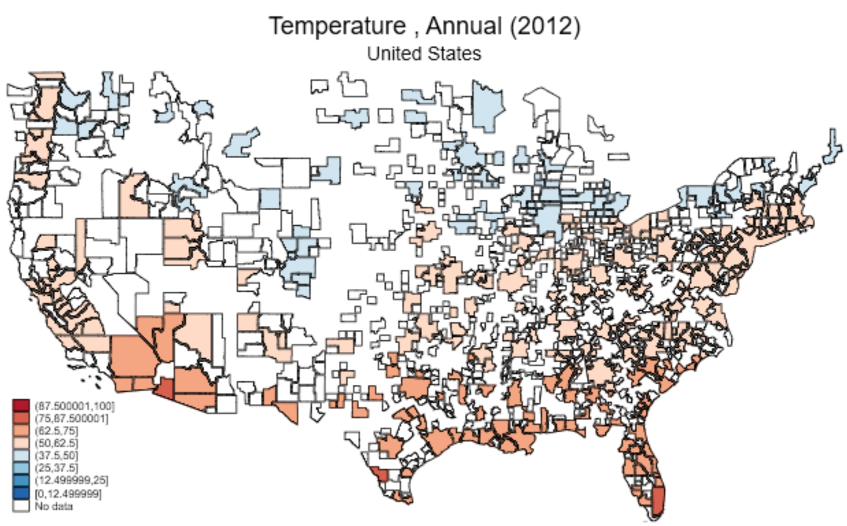

Figure G-18: Temperature Data on the collected MSAs in 2012

Source: Author's Calculation using ArcGIS and GSOD

Figures

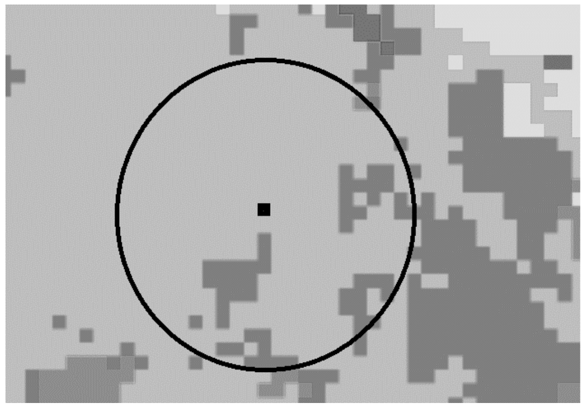

Figure F-1: NWALT Data (60m $\times$ 60m cells)

Source: Author's Calculation using ArcGIS

National 60-meter, 19-class mapping of anthropogenic land uses, with each 60m $\times$ 60m cell have a value that corresponds to a certain classification. In particular it allows to identify residential and commercial land use. This figure shows an enlarged section of the raster data. More information on classes and subclasses can be find in Falcone (2015).

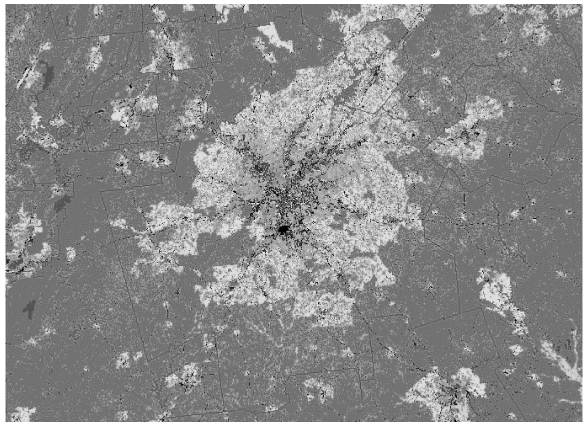

Figure F-2: Atlanta Metro Area

Source: Author's Calculation using ArcGIS

Metropolitan Statistical Area (MSA) lines are depected for the MSA by merging MSA vector data and NWALT. This Figure shows Atlanta Metropolitan area featuring 19 class land use.

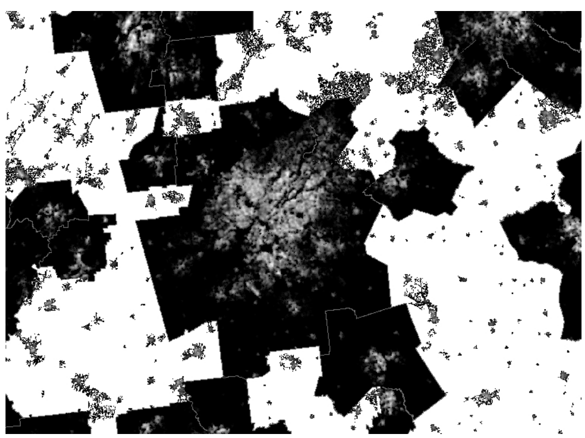

Figure F-3: Residential density pattern of Atlanta Metropolitan Area

Source: Author's Calculation using ArcGIS

For each residential cell flagged by the land use data, I have count number of residential cells in the neighborhood with 1 km radius. Then I divide it by the total number of cells in the neighborhood to get the percentage of residential area. This ratio then is assigned to the each residential cell. This figure shows the residential ratio in neighborhoods of each residential cell. Lighter areas shows more compact residential neighborhood relative to darker.

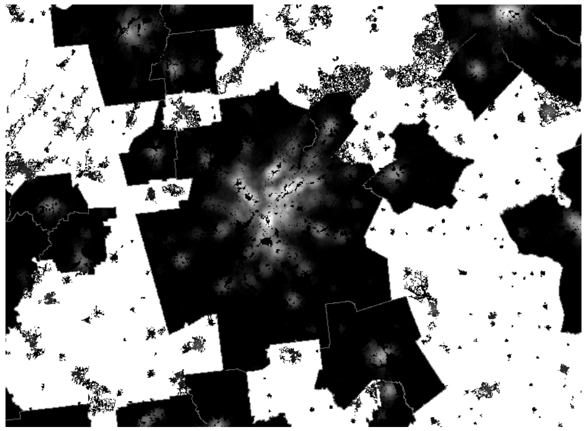

Figure F-4: Commercial density pattern of Atlanta Metropolitan Area

Source: Author's Calculation using ArcGIS

For each residential cell flagged by the land use data, I have count number of commercial cells in the neighborhood with 5 km radius. Then I divide it by the total number of cells in the neighborhood to get the percentage of commercial area. This ratio then is assigned to the each residential cell. This figure shows the commercial ratio in neighborhoods of each residential cell where lighter areas shows higher commercial accessibility relative to darker.

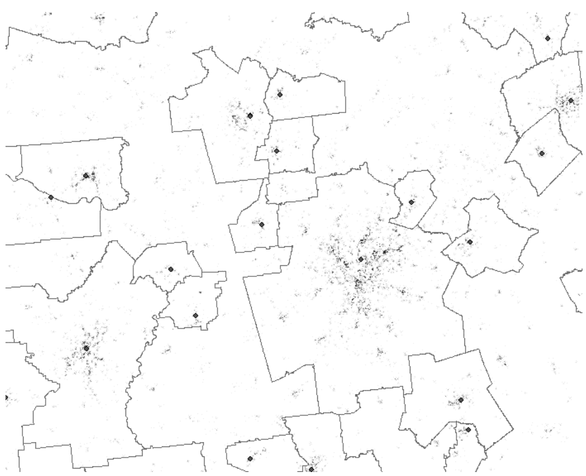

Figure F-5: Central business district

Source: Author's Calculation using ArcGIS

This figure shows CBD, define CBD as the center of the most concentrated circle with 5 km Radius in each metropolitan area. This allows me to find and assign a central point to each MSA that I will use for testing the heat island effect and its causes.

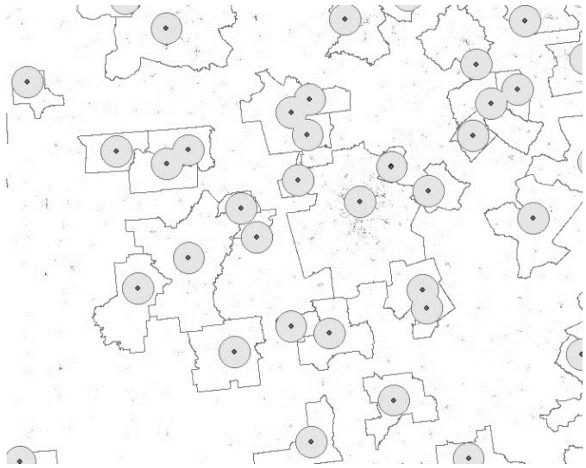

Figure F-6: City bound

Source: Author's Calculation using ArcGIS

This figure shows a 20 Km ring around each CBD as the inner city.

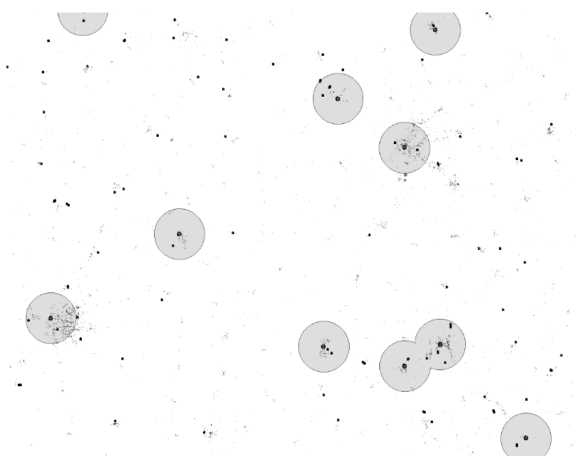

Figure F-7: Locating the weather stations on the map

Source: Author's Calculation using ArcGIS

This figure shows the location of weather station in the map. Merging all the data from the Vector MSA, Land use and GSOD and by linking the coordinates, I can locate the stations, in the neighborhood of each MSA center.

References

William Alonso et al. Location and land use. 1964.

Smart Growth America. Measuring sprawl 2014. *Washington, DC: Smart Growth America. Downloaded from http://www. smartgrowthamerica. org/documents/measuring-sprawl-2014. pdf on April*, 8:2014, 2014.

Shlomo Angel, Stephen Sheppard, Daniel L Civco, Robert Buckley, Anna Chabaeva, Lucy Gitlin, Alison Kraley, Jason Parent, and Micah Perlin. *The dynamics of global urban expansion*. Citeseer, 2005.

Nathaniel Baum-Snow. Did highways cause suburbanization? *The Quarterly Journal of Economics*, 122(2):775–805, 2007.

Basudeb Bhatta. *Analysis of urban growth and sprawl from remote sensing data*. Springer Science & Business Media, 2010.

J Thomas Black. The economics of sprawl. *Urban Land*, 55(3):6–52, 1996.

Ann Brown, Carrie Collins, Tim Frank, Kim Haddow, B Hitchings, S Parry, G Vanderpool, and L Wormser. Sprawl: The dark side of the american dream. *Sierra Club, San Francisco, CA*, 1998.

Marcy Burchfield, Henry G Overman, Diego Puga, and Matthew A Turner. Causes of sprawl: A portrait from space. *The Quarterly Journal of Economics*, 121(2):587–633, 2006.

Marion Clawson. Urban sprawl and speculation in suburban land. *Land economics*, 38(2): 99–111, 1962.

Andrew M Coutts, Jason Beringer, and Nigel J Tapper. Impact of increasing urban density on local climate: spatial and temporal variations in the surface energy balance in melbourne, australia. *Journal of Applied Meteorology and Climatology*, 46(4):477–493, 2007.

Andres Duany and Elizabeth Plater-Zyberk. The traditional neighborhood and suburban sprawl. *Urban planning*, 2003.

Gilles Duranton, Peter M Morrow, and Matthew A Turner. Roads and trade: Evidence from the us. *Review of Economic Studies*, 81(2):681–724, 2014.

Reid Ewing. Is los angeles-style sprawl desirable? *Journal of the American planning association*, 63(1):107–126, 1997.

Reid Ewing, Padma Haliyur, and G William Page. Getting around a traditional city, a suburban planned unit development, and everything in between. *Transportation Research Record*, 1466:53, 1994.

Reid Ewing, Rolf Pendall, and Don Chen. Measuring sprawl and its transportation impacts. *Transportation Research Record: Journal of the Transportation Research Board*, (1831): 175–183, 2003.

James A Falcone. Us conterminous wall-to-wall anthropogenic land use trends (nwalt), 1974–2012. Technical report, US Geological Survey, 2015.

Lance Freeman. The effects of sprawl on neighborhood social ties: An explanatory analysis. *Journal of the American Planning Association*, 67(1):69–77, 2001.

George Galster, Royce Hanson, Michael R Ratcliffe, Harold Wolman, Stephen Coleman, and Jason Freihage. Wrestling sprawl to the ground: defining and measuring an elusive concept. *Housing policy debate*, 12(4):681–717, 2001.

Edward L Glaeser and Matthew E Kahn. Sprawl and urban growth. In *Handbook of regional and urban economics*, volume 4, pages 2481–2527. Elsevier, 2004.

Peter Gordon and Harry W Richardson. Are compact cities a desirable planning goal? *Journal of the American planning association*, 63(1):95–106, 1997.

Robert O Harvey and William AV Clark. The nature and economics of urban sprawl. *Land Economics*, 41(1):1–9, 1965.

Elena G Irwin, Nancy E Bockstael, and Hyun Jin Cho. Measuring and modeling urban sprawl: Data, scale and spatial dependencies. In *Regional Science Association Meetings, Toronto, Canada, November*, 2006.

Stephen Malpezzi et al. Estimates of the measurement and determinants of urban sprawl in us metropolitan areas. Technical report, University of Wisconsin Center for Urban Land Economic Research, 1999.

Alberto Martilli. An idealized study of city structure, urban climate, energy consumption, and air quality. *Urban Climate*, 10:430–446, 2014.

David E Mills. Growth, speculation and sprawl in a monocentric city. *Journal of Urban Economics*, 10(2):201–226, 1981.

Tim R Oke. City size and the urban heat island. *Atmospheric Environment (1967)*, 7(8): 769–779, 1973.

Thomas Schueler. The importance of imperviousness. *Watershed protection techniques*, 1 (3):100–101, 1994.

Brian Stone and Michael O Rodgers. Urban form and thermal efficiency: how the design of cities influences the urban heat island effect. *American Planning Association. Journal of the American Planning Association*, 67(2):186, 2001.

Brian Stone, Jeremy J Hess, and Howard Frumkin. Urban form and extreme heat events: are sprawling cities more vulnerable to climate change than compact cities? *Environmental health perspectives*, 118(10):1425, 2010.

Qihao Weng, Hua Liu, and Dengsheng Lu. Assessing the effects of land use and land cover patterns on thermal conditions using landscape metrics in city of indianapolis, united states. *Urban ecosystems*, 10(2):203–219, 2007.

Anthony Gar-On Yeh and Xia Li. Measurement and monitoring of urban sprawl in a rapidly growing region using entropy. *Photogrammetric engineering and remote sensing*, 2001.

Zhu Zhongming, Zhang Wangqiang, Liu Wei, et al. Climate science special report: Fourth national climate assessment (nca4), volume i. 2017.

Appendix A Other Collected Atmospheric Climate Variables

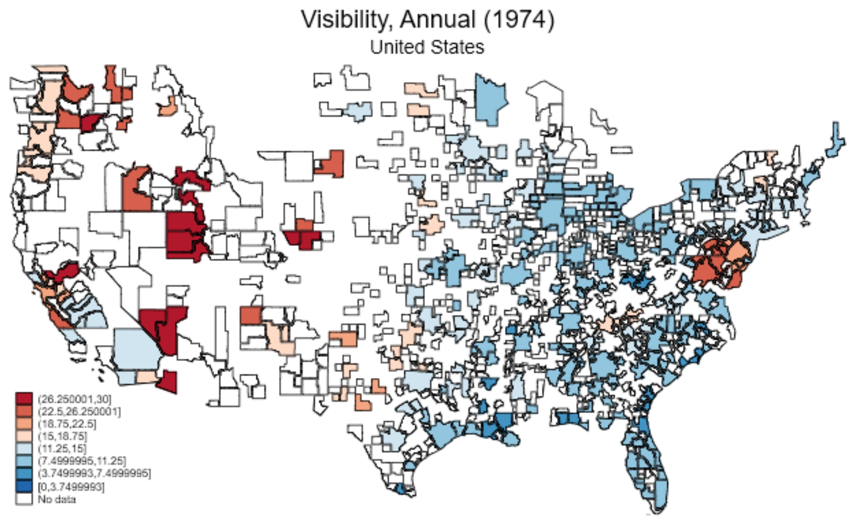

Figure F-8: GSOD data of Visibility in 1974

Source: Author's Calculation using ArcGIS and GSOD

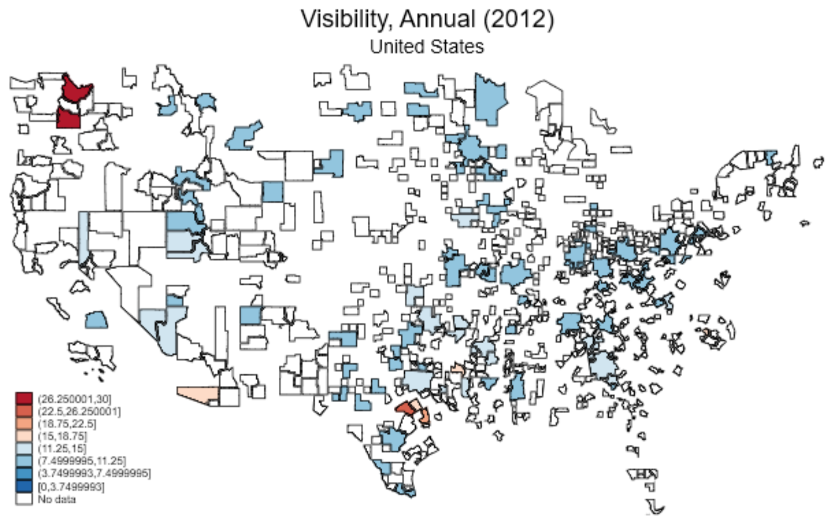

Figure F-9: GSOD data of Visibility in 2012

Source: Author's Calculation using ArcGIS and GSOD

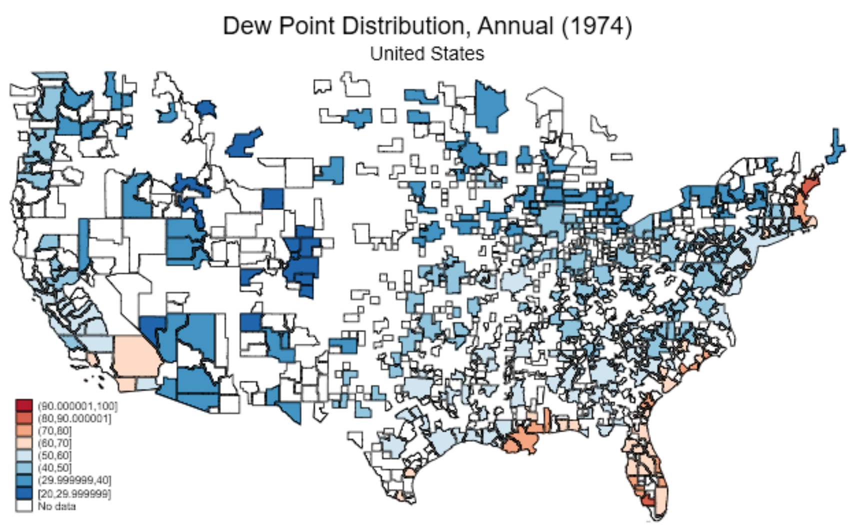

Figure F-10: GSOD data of Dew Point in 1974

Source: Author's Calculation using ArcGIS and GSOD

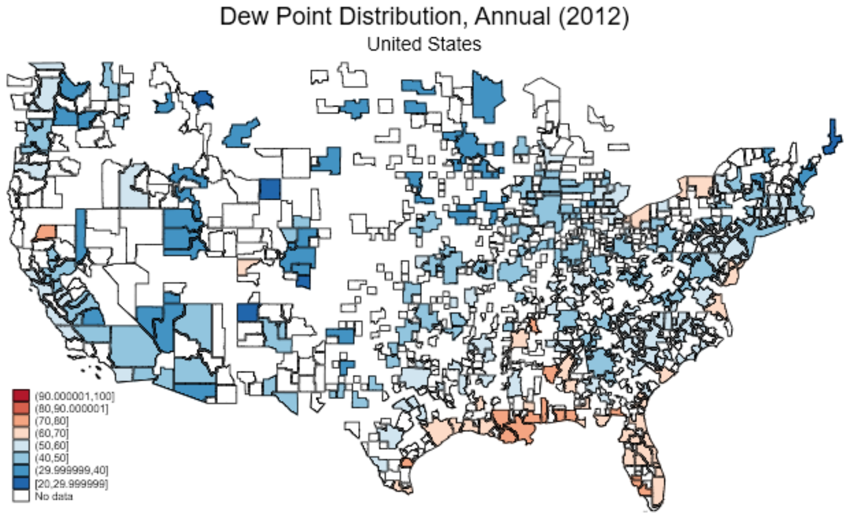

Figure F-11: GSOD data of Dew Point in 2012

Source: Author's Calculation using ArcGIS and GSOD

Table T-14: Correlation Analysis between residential compactness and multiple outcomes (Fixed Scheme)

	Annual	Winter	Spring	Summer	Autumn
Dew Point	-11.06	-3.23	-21.11	-9.51	-16.14
	(19.56)	(32.58)	(15.77)	(9.93)	(26.13)
Sea Level Pressure	-855.06	-764.94	-860.95	-837.2	-891.24
	(15128.97)	(14743.8)	(14835.2)	(15352.84)	(15438.08)
Station Pressure	-348.91	-614.68	-298.54	-274.63	-314.88
	(18931.47)	(22113.23)	(18135.3)	(21161.23)	(21299.23)
Visibility	-436.16	-396.41	-406.07	-427.81	-427.57
	(3573.08)	(3236.6)	(2932.93)	(3595.88)	(3708.14)
Wind Speed	-5.66	-4.46	-3.65	-7.56	-7.13
	(11.09)	(11.36)	(5.56)	(12.43)	(13.07)
Maximum Wind Speed	-177.85	-174.47	-153.61	-167.64	-174.7
	(1386.07)	(1371.74)	(732.95)	(1478.18)	(1549.57)
Gust	152.71	124.25	184.25	183.07	116.99
	(45.31)	(54.25)	(68.44)	(52.45)	(43.43)
Maximum Temperature of day	-1.52	.13	-11.62	16.67	-7.45
	(3.39)	(6.02)	(3.4)	(13.7)	(4.96)
Minimum Temperature of day	-.93	13.4	-9.67	-4.7	-1.82
	(2.62)	(4.97)	(2.23)	(3.77)	(4.7)
Percipitation	.3	.55	.38	.14	.16
	(.)	(.)	(.)	(.)	(.)
Temperature	-5.23	7.04	-14.99	-7.82	-4.69
	(3.19)	(5.11)	(1.86)	(4.59)	(5.01)

Standard errors in parentheses

Table T-15: Difference-in-Difference effects for Multiple outcomes and season/year (Fixed Scheme)

	Annual	Winter	Spring	Summer	Autumn
	Annual	Winter	Spring	Summer	Autumn
Dew Point	-1.49	-.7	-.92	-.89	-2.01
	(.65)	(.67)	(.59)	(.54)	(.76)
Sea Level Pressure	16.78	31.45	29.3	29.68	23.75
	(16.17)	(15.17)	(15.96)	(16.17)	(16.16)
Station Pressure	73.94	108.06	67.13	62.62	77.31
	(21.69)	(21.16)	(21.88)	(24.73)	(23.72)
Visibility	-41.14	-28.37	-33.81	-37.43	-41.27
	(7.91)	(6.72)	(7.43)	(7.84)	(7.91)
Wind Speed	.	.09	.14	.17	.05
	(.)	(.09)	(.09)	(.08)	(.08)
Maximum Wind Speed	3.46	4.6	2.91	3.95	3.69
	(1.54)	(1.59)	(1.4)	(1.52)	(1.49)
Gust	-.31	.47	-.75	.35	.47
	(.93)	(1.07)	(1.11)	(1.06)	(.98)
Maximum Temperature of day	.1	.07	-.04	-1.07	-.15
	(.33)	(.4)	(.42)	(.72)	(.38)
Minimum Temperature of day	.44	.09	.44	.62	.24
	(.33)	(.4)	(.31)	(.31)	(.46)
Percipitation	-.01	-.02	-.02	-.01	-.01
	(.01)	(.01)	(.01)	(.01)	(.01)
Temperature	.59	.12	.52	.59	.12
	(.27)	(.35)	(.29)	(.27)	(.38)
Number of Hot Days	-.01				
	(.16)				
Number of Very Hot Days	.72				
	(.67)				

Standard errors in parentheses
Causal Effect of Residential Compactness on Multiple Environmental Dimensions for the center of middle size MSAs.

Table T-16: Instrumental Variable estimates of the multiple outcomes (Fixed Scheme)

	Annual	Winter	Spring	Summer	Autumn
Dew Point	-3.47	15.22	-34.09	-13.55	-23.06
	(11.35)	(14.67)	(10.21)	(8.05)	(13.3)
	39.66	41.73	43.67	42.36	36.23
Sea Level Pressure	-870.92	-1035.24	-849.04	-923.61	-1023.09
	(276.65)	(274.83)	(275.36)	(278.02)	(280.93)
	16.81	17.08	15.90	18.36	17.38
Station Pressure	-1036.73	-1896.37	-1124.61	-936.87	-1042.03
	(370.62)	(404.4)	(362.33)	(391.38)	(394.08)
	32.15	25.69	34.93	33.91	30.13
Visibility	-493.04	-442.23	-420.78	-471.35	-452.19
	(142.49)	(130.66)	(121.23)	(139.68)	(143.82)
	6.33	8.28	6.91	7.83	7.87
Wind Speed	2.86	5.59	6.76	-1.97	-.63
	(8.29)	(8.48)	(5.82)	(8.8)	(9.07)
	6.86	11.44	8.21	10.22	10.38
Maximum Wind Speed	-136.8	-148.43	-93.97	-150.05	-162.33
	(93.44)	(91.86)	(68.03)	(96.12)	(98.33)
	4.70	8.94	4.39	8.65	8.17
Gust	215.13	159.38	284.18	261.54	132.54
	(17.66)	(18.92)	(22.19)	(19.24)	(16.96)
	12.45	10.95	9.86	11.79	17.88
Maximum Temperature of day	-9.35	4.63	-32.68	21.66	-18.52
	(4.75)	(6.3)	(4.91)	(9.7)	(5.67)
	161.12	254.99	99.31	31.61	181.51
Minimum Temperature of day	-7.25	27.57	-22.07	-22.22	-21.25
	(4.11)	(5.81)	(3.88)	(5.02)	(5.63)
	224.90	207.90	209.06	94.68	132.12
Percipitation	.61	1.39	.99	.19	.13
	(.09)	(.14)	(.14)	(.15)	(.08)
	9.85	7.10	6.71	4.44	11.37
Temperature	-14.35	14.37	-29.6	-21.71	-24.27
	(4.53)	(5.83)	(3.55)	(5.49)	(5.77)
	186.73	235.62	229.69	65.90	139.54
Number of Hot Days	-15.02				
	(5.23)				
	97.01				
Number of Very Hot Days	1.61				
	(2.74)				
	17.67				

Standard errors in parentheses and third row represents F-statistic for the 1^{st} stage.
Causal Effect of Residential Compactness on Multiple Environmental Dimensions for the center of middle size MSAs.

Table T-17: Analysis of the sensitivity of the control group to the Instrument (Fixed Scheme)

	Annual	Winter	Spring	Summer	Autumn
Dew Point	-44.64	-26.48	-57.45	-37.1	-57.58
	(9.27)	(11.25)	(8.5)	(6.6)	(10.68)
	22.17	26.22	25.59	25.78	20.55
Sea Level Pressure	-1197.23	-1044.76	-1044.99	-1077.67	-1224.74
	(237.43)	(233.98)	(238.66)	(237.69)	(239.99)
	14.84	15.12	14.77	15.06	14.67
Station Pressure	-469.89	-597.33	-450.14	-487.45	-407.39
	(223.59)	(235.91)	(220.84)	(228.63)	(233.88)
	21.29	17.98	23.77	23.60	19.68
Visibility	-1041.94	-920.54	-959.54	-1029.64	-1005.35
	(122.87)	(114.02)	(119.24)	(123.01)	(122.02)
	7.88	8.11	8.29	8.34	8.08
Wind Speed	.	3.7	1.28	-4.12	-1.88
	(.)	(1.76)	(2.15)	(2.39)	(2.23)
	0.00	2.45	3.05	2.54	1.81
Maximum Wind Speed	-100.29	-91.67	-126.12	-127.98	-122.71
	(20.64)	(26.37)	(27.92)	(32.64)	(33.72)
	17.35	10.43	7.74	7.75	6.75
Gust	177.79	153.72	224.64	210.65	133.08
	(13.69)	(14.11)	(16.39)	(15.11)	(12.62)
	9.55	7.96	9.25	10.31	12.61
Maximum Temperature of day	-10.77	-.32	-18.36	-5.59	-23.65
	(3.31)	(4.5)	(4.42)	(5.57)	(3.86)
	192.82	266.95	79.83	20.07	206.52
Minimum Temperature of day	-2.16	21.62	-14.27	-7.64	-9.13
	(2.79)	(4.43)	(3.29)	(2.75)	(3.96)
	248.49	185.59	153.51	145.09	131.39
Percipitation	.33	.67	.46	.07	.07
	(.05)	(.08)	(.08)	(.07)	(.05)
	14.59	10.60	9.49	8.93	12.33
Temperature	-5.84	12.77	-23.11	-12.46	-13.89
	(2.58)	(4.01)	(3.12)	(2.78)	(3.45)
	307.16	264.14	173.56	119.68	201.81
Number of Hot Days	-3.66				
	(3.4)				
	5.22				
Number of Very Hot Days	.54				
	(1.74)				
	19.02				

Standard errors in parentheses and third row represents F-statistic for the 1^{st} stage.

Table T-18: Corrected causal effect of residential compactness on multiple outcomes, using hybrid method (Fixed Scheme)

	Annual	Winter	Spring	Summer	Autumn
Dew Point	48.43	47.32	40.95	31.53	48.5
	(14.69)	(17.72)	(13.1)	(10.09)	(16.06)
	14.11	16.07	14.11	16.07	15.79
Sea Level Pressure	473.7	104.9	285.33	295.54	411.64
	(383.56)	(379.37)	(384.3)	(386.04)	(390.07)
	256.00	12.80	11.25	12.58	12.25
Station Pressure	-589.24	-1288.44	-684.4	-398.68	-560.89
	(338.22)	(352.89)	(330.37)	(371.72)	(370.2)
	24.69	21.28	23.75	23.95	23.90
Visibility	738.64	651.74	706.42	715.24	715.62
	(200.98)	(184.57)	(179.51)	(198.25)	(203.57)
	7.05	8.42	8.56	8.44	8.06
Wind Speed	2.86	1.39	5.8	4.03	.92
	(8.29)	(8.74)	(6.44)	(9.35)	(9.54)
	6.86	10.55	6.64	9.48	9.02
Maximum Wind Speed	38.72	21.19	59.07	19.35	-3.46
	(95.88)	(96.72)	(75.11)	(105.21)	(106.88)
	5.56	9.25	6.03	7.94	7.52
Gust	-13.09	-31.16	-5.2	-18.16	-37.89
	(15.72)	(16.98)	(19.62)	(16.83)	(15.61)
	8.11	7.78	6.12	6.93	9.60
Maximum Temperature of day	-4.8	.16	-21.02	16.16	3.51
	(4.99)	(3.12)	(5.79)	(7.6)	(4.33)
	10.64	33.65	7.60	35.57	19.46
Minimum Temperature of day	-7.66	-1.96	-6.12	-13.36	-9.4
	(4.36)	(3.68)	(4.16)	(4.82)	(4.21)
	20.16	29.94	18.30	19.00	23.62
Percipitation	.16	.49	.33	.05	.04
	(.09)	(.12)	(.13)	(.15)	(.07)
	5.73	2.84	3.92	3.14	7.00
Temperature	-10.75	-3.93	-5.11	-8.59	-9.35
	(4.81)	(3.32)	(3.23)	(5.24)	(4.52)
	13.89	25.06	21.70	18.10	15.73
Number of Hot Days	.				
	(.)				
	0.00				
Number of Very Hot Days	.				
	(.)				
	0.00				

Standard errors in parentheses and third row represents F-statistic for the 1^{st} stage.

Table T-19: Correlation Analysis between residential compactness and multiple outcomes (Flexible Scheme)

	Annual	Winter	Spring	Summer	Autumn
Dew Point	-11.06	-3.23	-21.11	-9.51	-16.14
	(19.56)	(32.58)	(15.77)	(9.93)	(26.13)
Sea Level Pressure	-855.06	-764.94	-860.95	-837.2	-891.24
	(15128.97)	(14743.8)	(14835.2)	(15352.84)	(15438.08)
Station Pressure	-348.91	-614.68	-298.54	-274.63	-314.88
	(18931.47)	(22113.23)	(18135.3)	(21161.23)	(21299.23)
Visibility	-436.16	-396.41	-406.07	-427.81	-427.57
	(3573.08)	(3236.6)	(2932.93)	(3595.88)	(3708.14)
Wind Speed	-5.66	-4.46	-3.65	-7.56	-7.13
	(11.09)	(11.36)	(5.56)	(12.43)	(13.07)
Maximum Wind Speed	-177.85	-174.47	-153.61	-167.64	-174.7
	(1386.07)	(1371.74)	(732.95)	(1478.18)	(1549.57)
Gust	152.71	124.25	184.25	183.07	116.99
	(45.31)	(54.25)	(68.44)	(52.45)	(43.43)
Maximum Temperature of day	-1.52	.13	-11.62	16.67	-7.45
	(3.39)	(6.02)	(3.4)	(13.7)	(4.96)
Minimum Temperature of day	-.93	13.4	-9.67	-4.7	-1.82
	(2.62)	(4.97)	(2.23)	(3.77)	(4.7)
Percipitation	.3	.55	.38	.14	.16
	(.)	(.)	(.)	(.)	(.)
Temperature	-5.23	7.04	-14.99	-7.82	-4.69
	(3.19)	(5.11)	(1.86)	(4.59)	(5.01)

Standard errors in parentheses

Table T-20: Difference-in-Difference effects for Multiple outcomes and season/year (Flexible Scheme)

	Annual	Winter	Spring	Summer	Autumn
Dew Point	-1.52	-.89	-.93	-.87	-1.97
	(.64)	(.68)	(.59)	(.53)	(.75)
Sea Level Pressure	41.22	50.96	52.29	53.8	47.3
	(16.09)	(15.42)	(15.9)	(16.1)	(16.07)
Station Pressure	75.03	109.34	67.75	63.34	78.71
	(21.8)	(21.33)	(22.)	(24.72)	(23.71)
Visibility	-41.26	-29.46	-33.7	-37.82	-41.31
	(7.63)	(6.81)	(7.18)	(7.55)	(7.64)
Wind Speed	.	.06	.12	.2	.03
	(.)	(.09)	(.09)	(.08)	(.08)
Maximum Wind Speed	3.48	4.32	2.57	3.93	3.82
	(1.55)	(1.6)	(1.41)	(1.52)	(1.49)
Gust	-.27	.3	-.4	.36	.47
	(.94)	(1.09)	(1.12)	(1.07)	(.99)
Maximum Temperature of day	.04	.	-.08	-1.06	-.19
	(.33)	(.41)	(.42)	(.72)	(.39)
Minimum Temperature of day	.47	.06	.49	.69	.31
	(.34)	(.41)	(.32)	(.32)	(.47)
Percipitation	-.01	-.02	-.02	-.01	-.01
	(.01)	(.01)	(.01)	(.01)	(.01)
Temperature	.56	.07	.5	.6	.13
	(.28)	(.36)	(.29)	(.27)	(.39)
Number of Hot Days	.01				
	(.16)				
Number of Very Hot Days	.59				
	(.66)				

Standard errors in parentheses
Causal Effect of Residential Compactness on Multiple Environmental Dimensions for the center of middle size MSAs.

Table T-21: Instrumental Variable estimates of the multiple outcomes (Flexible Scheme)

	Annual	Winter	Spring	Summer	Autumn
Dew Point	-9.1	9.03	-37.07	-14.14	-29.78
	(11.17)	(14.42)	(10.07)	(7.96)	(12.94)
	40.63	43.22	46.46	45.18	38.70
Sea Level Pressure	-819.84	-942.01	-806.35	-853.65	-909.08
	(310.57)	(306.55)	(307.33)	(312.92)	(313.79)
	13.39	13.90	13.74	14.59	14.42
Station Pressure	-1347.72	-2001.28	-1385.18	-1193.89	-1336.79
	(352.71)	(384.5)	(346.1)	(371.58)	(373.75)
	33.19	26.52	35.63	35.14	31.87
Visibility	-571.28	-517.13	-497.21	-524.72	-536.08
	(151.15)	(143.73)	(136.75)	(151.55)	(153.93)
	5.69	8.64	5.38	8.39	8.44
Wind Speed	-3.88	.39	-.82	-9.4	-7.55
	(8.41)	(8.51)	(5.95)	(8.91)	(9.13)
	6.92	11.04	8.19	9.76	10.65
Maximum Wind Speed	-179.11	-179.93	-140.83	-198.34	-204.36
	(94.)	(93.45)	(68.31)	(97.11)	(99.43)
	4.72	8.03	4.63	7.85	8.07
Gust	206.11	154.12	274.66	249.61	128.38
	(17.31)	(18.67)	(21.58)	(18.73)	(16.66)
	12.64	11.33	10.67	12.32	17.83
Maximum Temperature of day	-7.07	6.95	-31.05	17.13	-17.3
	(4.66)	(6.2)	(4.8)	(9.35)	(5.65)
	160.54	246.28	99.33	24.97	171.22
Minimum Temperature of day	-9.28	24.24	-22.68	-22.73	-24.01
	(4.12)	(5.66)	(3.85)	(5.02)	(5.64)
	205.23	200.56	197.21	86.87	118.30
Percipitation	.63	1.36	1.	.26	.12
	(.09)	(.14)	(.13)	(.14)	(.08)
	8.80	6.81	6.54	4.43	9.85
Temperature	-13.34	14.72	-26.23	-22.99	-23.39
	(4.54)	(5.72)	(3.51)	(5.49)	(5.77)
	173.12	226.27	219.26	62.83	126.96
Number of Hot Days	-12.34				
	(4.83)				
	64.31				
Number of Very Hot Days	1.				
	(2.76)				
	17.79				

Standard errors in parentheses and third row represents F-statistic for the 1^{st} stage.
Causal Effect of Residential Compactness on Multiple Environmental Dimensions for the center of middle size MSAs.

Table T-22: Analysis of the sensitivity of the control group to the Instrument (Flexible Scheme)

	Annual	Winter	Spring	Summer	Autumn
Dew Point	-47.8	-31.32	-56.91	-40.33	-62.54
	(9.3)	(11.53)	(8.5)	(6.72)	(10.83)
	20.03	23.09	22.73	22.19	18.39
Sea Level Pressure	-876.73	-776.13	-763.01	-777.01	-903.35
	(221.36)	(220.6)	(223.67)	(223.23)	(223.29)
	15.57	15.43	15.37	15.58	15.42
Station Pressure	-361.26	-481.67	-315.09	-364.71	-341.59
	(220.82)	(231.04)	(220.27)	(228.16)	(229.63)
	23.76	20.65	25.84	25.71	22.38
Visibility	-973.52	-824.63	-920.88	-1001.85	-939.99
	(116.94)	(109.63)	(116.46)	(119.98)	(116.5)
	8.43	8.42	8.43	8.53	8.45
Wind Speed	.	4.55	2.03	-3.23	-2.27
	(.)	(1.78)	(1.73)	(1.96)	(2.15)
	0.00	2.23	3.48	3.03	1.65
Maximum Wind Speed	-73.43	-55.89	-104.1	-146.94	-110.27
	(18.96)	(25.13)	(23.52)	(39.82)	(32.7)
	19.26	10.94	10.84	5.37	7.38
Gust	147.53	127.15	183.42	167.11	104.29
	(12.89)	(13.51)	(15.29)	(14.04)	(12.17)
	10.50	8.34	9.89	10.71	13.24
Maximum Temperature of day	-15.84	-3.65	-30.39	-6.87	-26.56
	(3.18)	(4.39)	(3.4)	(5.48)	(3.85)
	196.71	263.08	124.47	20.25	194.71
Minimum Temperature of day	-3.22	20.	-8.01	-3.42	-10.06
	(2.67)	(4.23)	(2.7)	(2.54)	(3.9)
	245.73	186.78	209.50	158.54	122.92
Percipitation	.35	.63	.5	.12	.1
	(.05)	(.08)	(.08)	(.08)	(.05)
	13.92	10.18	8.85	8.26	11.17
Temperature	-7.99	10.51	-17.53	-7.89	-15.58
	(2.5)	(3.87)	(2.72)	(2.67)	(3.43)
	300.29	261.74	208.96	121.38	188.03
Number of Hot Days	-2.36				
	(2.87)				
	6.29				
Number of Very Hot Days	.57				
	(1.73)				
	18.42				

Standard errors in parentheses and third row represents F-statistic for the 1^{st} stage.

Table T-23: Corrected causal effect of residential compactness on multiple outcomes, using hybrid method (Flexible Scheme)

	Annual	Winter	Spring	Summer	Autumn
Dew Point	48.44	49.45	38.72	36.25	49.92
	(14.58)	(18.04)	(13.11)	(10.24)	(16.14)
	15.01	16.72	15.80	17.22	16.99
Sea Level Pressure	.49	-216.42	-107.42	-119.32	11.07
	(370.35)	(363.8)	(366.18)	(373.49)	(370.66)
	256.00	13.71	12.45	13.08	13.31
Station Pressure	-1035.32	-1525.96	-1099.47	-822.01	-959.3
	(334.12)	(343.07)	(319.19)	(360.86)	(359.62)
	24.63	21.91	24.60	24.39	24.71
Visibility	568.97	457.67	595.79	643.2	553.66
	(199.23)	(193.42)	(188.32)	(204.78)	(206.24)
	6.68	7.65	6.93	8.19	7.91
Wind Speed	-3.88	-4.82	-2.75	-4.28	-5.75
	(8.41)	(8.82)	(6.31)	(9.25)	(9.43)
	6.92	10.09	7.17	9.60	9.87
Maximum Wind Speed	-36.59	-52.01	-17.09	6.34	-63.12
	(95.81)	(97.96)	(72.3)	(111.76)	(105.91)
	5.56	8.42	6.81	6.85	7.92
Gust	21.35	2.03	44.2	31.79	-1.73
	(15.29)	(16.38)	(18.97)	(16.87)	(15.44)
	8.92	9.45	8.37	8.25	10.47
Maximum Temperature of day	5.08	6.98	-1.82	13.46	9.21
	(4.78)	(3.07)	(3.89)	(7.51)	(4.37)
	10.81	33.89	21.08	22.64	18.35
Minimum Temperature of day	-8.18	-3.51	-15.66	-19.61	-10.65
	(4.29)	(3.48)	(3.58)	(4.75)	(4.21)
	18.03	31.35	25.79	18.74	22.74
Percipitation	.15	.51	.27	.07	.
	(.09)	(.12)	(.13)	(.14)	(.08)
	5.75	2.94	4.26	3.41	6.64
Temperature	-6.69	-.84	-9.78	-16.35	-5.81
	(4.8)	(3.22)	(3.02)	(5.3)	(4.56)
	12.60	25.06	29.31	19.30	14.07
Number of Hot Days	.				
	(.)				
	0.00				
Number of Very Hot Days	.				
	(.)				
	0.00				

Standard errors in parentheses and third row represents F-statistic for the 1^{st} stage.