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Title: Estimating the Influence of the Urban Heat Island Effect on Housing Prices

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Using summertime housing transactions data of 3,309 parcels from multiple years in Eugene-Springfield, OR, we present a hedonic price model to estimate the influence of the urban heat island (UHI) effect on housing prices in this metropolitan area. By taking advantage of the inherent random nature of summertime weather observations, we create measures of the UHI that isolate this effect from other housing amenities and dis-amenities in our sample area. We test several model specifications for our pooled-cross sectional data by including lag temperature deviation variables, interaction terms, yearly and monthly fixed effects, and two alternative types of neighborhood fixed-effects at census block level and PRISM Grid to further control for any unobservables that cause bias in the estimates. We contribute to existing literature of the valuation of climate amenities and find that the UHI effect has an economically significant and negative influence on housing prices. In particular, we find that houses sell at a discount during abnormally hot periods in the summer. The implications of our findings provide insight on how home buyers are influenced by hot temperatures that exacerbate the UHI effect, which also informs policymakers, home sellers, and other housing market professionals as to potential climate change consequences faced by growing metropolitan areas.

Estimating the Influence of the Urban Heat Island Effect on Housing Prices

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APPROVED:

Major Professor, representing Applied Economics

Head of the Department of Applied Economics

Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Lima Hossain, Author

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Chapter 1

Introduction

Increased greenhouse gas emissions have contributed to rising global temperatures in recent years, encouraging adaptation and make lifestyle changes in various human systems. The hazards of extreme temperatures impact health and economic livelihoods, especially within urban areas. Due to climate change, heat waves have become longer and more frequent with extreme heat causing higher mortality rates than any other natural disasters (Harris 2020; Baker 2019). The frequency and longevity of these heat waves create a climate phenomenon in metropolitan areas known as the urban heat island (UHI) effect. In a recent issue of Time Magazine, the UHI effect in Jacobabad, Pakistan, is highlighted as the city reached 124°F, weather causing respiratory distress and heatstroke for residents living there. In addition, to the negative health effects, the UHI effects also compromises economic productivity as people are unable to work during the day; the extreme heat is retained in the environment which also prevents cooling down at night (Graff and Neidell 2014). There is also evidence that low-income communities face the greatest risk as they lack the resources needed to voluntarily evacuate during extreme weather events (Hollis 2019). Extreme heat impacts the most vulnerable populations in our society, providing a strong motivation for policy proposals aimed at mitigating greenhouse gas emissions in the atmosphere and adaptation with environmental justice principles.

Although humans are highly adaptive when it comes to heat, there is a limit since the body cools down by sweating which is less effective when the air is already humid and hot (Baker 2019). The UHI effect experienced in cities creates a core of warmer temperatures up to 10-20 degrees warmer compared to its surrounding areas (Shandas et. al 2016). The construction density, human activity, traffic congestion, and lack of green/open space all contribute to the retainment of extreme heat in the area. The infrastructure in cities often intensify this effect because the dry, impermeable surfaces of asphalt and concrete get much hotter compared to areas with more trees, moisture, and shade, which provide a cooling effect in the environment. In addition, cities also tend to produce more industrial heat from cars and air conditioning which further exacerbates the UHI effect. On a national scale, summers in the U.S. have been hotter since the 1970's and daily temperatures in metro areas are 27°F higher than surrounding rural areas for 60 major cities (Kenward et. al 2014). Within these cities, Portland, OR ranks amongst the top 5 cities in the U.S. that is impacted by the urban heat island effect. With an increase in the intensity and frequency of hotter weather extremes, some cities have implemented ordinances that require A/C capabilities in rental units (Harris 2020; Kaplan 2020). However, a major concern that arises from this is the energy burden, which is defined in Oregon as the percent of the household income spent on energy bills (Oregon Department of Energy 2019). This encourages homeowners to implement energy efficient systems which reduces the cost of utilities, greenhouse gas emissions, energy consumption and improves the overall health and safety of the household. Households that have a higher energy burden benefit from easing this since they are also less able to invest in efficiency solutions for their homes. Another approach to mitigate these climate change effects within the urban development setting, is through the implementation of urban and peri-urban forests which create a microclimate that absorbs carbon dioxide and dust particles and provides a more direct cooling effect. A recent call for action by the Food and Agriculture Organization of the United Nations (FAO) demonstrates how cities can use forest-based solutions as a more sustainable and resilient model of urban development, making cities greener and healthier places to live (Borelli and Conigliaro 2020). Studying the impacts of climate change illustrates the multi-scale nature of the UHI effect, which is related to lifestyle and policy changes both nationally and globally.

1.1 Research Focus

We refined our area of interest for this study to the neighboring cities of Eugene-Springfield, OR in an effort to quantify the urban-heat island effect on housing markets. The variation of the magnitude of monthly temperature deviations from normal climate outcomes within a single metropolitan area allows us to tease out the potential UHI effect on housing prices. Economists have long studied how environmental amenities and dis-amenities impact housing prices and this literature provides a foundation for designing a plausibly exogenous measure of the urban heat island and determine whether it impacts housing price transactions (Ohler and Blanco 2017; Klaiber and Abbott 2011; Montero et. al 2017; Albouy et. al 2016). Traditionally, the hedonic price model established by Rosen (1967) is used to capture the value of homes as it reflects an individual’s willingness to pay (WTP) for changes in climate and housing amenities/dis-amenities that are location-specific and heterogenous across cities (Albouy et. al 2016). For example, proximity to open/green space has been shown to be an environmental amenity in the Netherlands (Daams et. al 2016) while proximity to airports has been shown to be an environmental dis-amenity in Memphis, TN (Affuso et. al 2019). By valuing climate amenities, we can see how warmer temperatures affect individual behavior in the housing market, which provides insights into the interaction between climate and location decisions and informs policy.

1.2 Capturing Measures of the Urban Heat Island Effect

We capture measures of the UHI in our hedonic model by looking at the temperature deviation from monthly average and maximum daily temperatures compared to historical climate normals during summer months. Our identification strategy relies on neighborhood and temporal fixed effects along with the randomness of weather observations to isolate the UHI effect from other local amenities that may also impact housing prices. Because climate can be perceived from the actual experience of weather, the short-run response to a change in climate can be estimated from the effects of weather fluctuations which is known as the marginal treatment comparability assumption (Hsiang 2016). Bishop et. al (2019, 2) state that the best practice in using hedonic property models for welfare measurement relies on a research design that identifies a clear source of exogenous variation in an amenity such as weather, that prospective buyers can be assumed to observe. This ensures that our UHI measures are indeed random and exogenous in our model since the weather —and hot spells in particular—is salient and observable to a home buyer in the negotiation process. Additionally, we implement two types of neighborhood fixed effects to isolate the weather influence of the UHI. These neighborhood fixed effects control for time-invariant unobservables, like parks or biking trails, that are specific to neighborhoods. We also consider the spatial nature of the housing data and use GIS analysis to create a database of housing and climate variables for our sample. Omitted variable bias is a common concern with any hedonic price model and we explore this through different specifications of the UHI measure, temperature lag variables, interaction terms, and add controls for inflation in the housing market, seasonality, and neighborhood amenities, ultimately testing the robustness of our estimates. We find that the overall UHI effect has a negative and economically significant influence on housing prices in our sample. This thesis contributes to the literature by borrowing approaches from agricultural, environmental, and climate economics to capture a measure of the heat island effect while keeping the spatial integrity of the housing data.

Chapter 2

Hedonic Price Model and Environmental Amenities/Dis-Amenities

The decomposition of the valuation of a home into the individual attributes describing the home is traditionally modeled using a hedonic price method, pioneered by Rosen (1974). Under the assumptions of his model, a house is considered to be a composite good, in which the price of a home, P, is reflective of its housing attributes which are represented as a bundle of goods. The relationship between the price of a differentiated product and its attributes is interpreted as an equilibrium outcome that occurs from the market interactions between the consumer and producer. By regressing the price of a product on its attributes, a consumer's preference represented as the marginal willingness (MWTP) to pay for individual attributes of a differentiated product, such as a house is revealed, equation 1.

$$P = f(size, location, type, rooms, neighborhood\ characteristics, etc) \quad [1]$$

In addition, the hedonic model of market equilibrium implies that changes in non-market goods and services can be conveyed through the location choice of a home (Scott Orford 1999). The market prices for housing reveal a consumers' willingness to pay (WTP) for location specific housing attributes. Neighborhood and environmental amenities such as parks, better air quality, proximity to recreational spaces, minimal noise pollution are a few attributes that have been studied in the literature providing insight on how consumers value environmental amenities and dis-amenities (Daams et. al 2016; Montero et. al 2017; Affuso et. al 2019).

2.1 Model Specification of Hedonic Price Models

A recent study by Kuminoff et. al (2010) shows evidence that moving away from standard linear specifications of the price function improves the accuracy of estimating the effects of attributes on the value of a home. They argue that a flexible framework that utilizes a combination of spatial fixed effects, quasi-experimental identification, and temporal controls for housing market adjustment is needed to address the omitted variable bias problem. While this problem is quite general, it is challenging to evaluate its implications for hedonic estimates of nonmarket values because housing prices and consumer welfare are simultaneously determined as equilibrium outcomes of the market clearing process (Rosen 1974). In order to address this bias, Kuminoff et. al (2010), implement a theoretically consistent series of Monte Carlo simulations to evaluate the performance of the hedonic price method in determining MWTP for reduced commute time and proximity to a park. Using housing transactions data for Wake County, North Carolina they simulate 54,000 regressions to evaluate 540 different hedonic models in various functional forms. The models varied according to the shape of the utility function (Cobb–Douglas, Translog, Diewert); the form of the price function (linear, log–linear, log–log, Box–Cox linear, quadratic, Box–Cox quadratic); the spatial controls for omitted variables (no controls, fixed effects for census tracts, spatial error model, spatial lag model); the approach to panel data estimation (pooled cross-section, differences-in-differences, first differences); the variables omitted from the regression (none, three neighborhood amenities, three randomly chosen variables); and the number of homes in the simulated market (200, 2000) (p153). By preserving the spatial characteristics of the urban landscape in their simulations, they state that pseudo-data reflects spatial correlation between prices, neighborhood attributes, and amenities in their study area. They further control for neighborhood amenities by implementing census tract spatial fixed effects and generate weight matrices for estimating spatial lag and spatial error models based on the geographical coordinates of a housing parcel.

The results of their simulations indicate that a model estimated using OLS with no omitted variables contain 25% bias in linear functional form, 24% bias in semi-log functional form, and 42% bias in log-log functional form for cross sectional data. This bias is reduced to 18% when spatial fixed effects are added to an OLS model in semi-log form indicating that adding controls for neighborhood amenities strengthen model specification. Lastly, they find that a difference-in-difference estimator performs the best for panel data with 16% bias when a model is in semi-log form. One advantage of the data used for their simulations is that it contains repeated sales of the same home at various periods in time which reduces bias caused from time constant omitted variables.

Kuminoff et al. (2010) add insight on controlling for omitted variable bias by taking advantage of their data structure, preserving spatial attributes of housing parcels, and implementing spatial fixed effects and spatial lags in their hedonic models. Given the evidence that more flexible specifications for the price function outperform the simpler linear models in this study, we test both linear and log-linear functional forms in our model specifications. We also implement spatial fixed effects at the census tract level to further control for the presence of bias caused by omitted variables. Our dataset also contains repeated sales from the same neighborhoods over a 4-year sample period allowing us to take advantage of the structure of our data to alleviate the presence of bias that may arise from time-constant omitted neighborhood variables. By measuring the amount of bias in different combinations of functional forms and estimation methods, Kuminoff et. al (2010) provide a guideline for model specification that captures the non-market values of public goods, environmental services, and urban amenities.

2.2 Omitted Variable Bias and Multiscale Capitalization in Hedonic Price Models

Another study conducted by Klaiber and Abbott (2011) explores the issue of omitted variable bias in hedonic price models by delving further into the different types of fixed effects that can be used in specification. They argue that the traditional fixed effects that approximate some notion of a neighborhood are not enough to capture unobserved variables that occur at different spatial scales. Although fine spatial fixed effects improve estimates, they believe that the bias is due to the subsuming of capitalization into fixed effects for nonmarket goods. In contrast, they also recognize that many studies use “coarse” effects at the city, county or school level to capture the capitalization of amenities but at the cost of potential omitted variable bias. “For example, while school districts are likely to be an appropriate scale to evaluate differences in school quality, fixed effects at such a large spatial scale will fail to capture potentially important unobservable spatial variation correlated with measures of school quality that vary across the neighborhoods comprising the district” (Klaiber and Abbott, 2011, 1332). This acknowledges that researchers may be encouraged to use finer scale fixed effects but a limitation of this is that district wide capitalization of school quality would not be properly measured.

To illustrate the tradeoff between controlling for omitted variables and measurement of the full extent of capitalization, they create measures of adjacency to sub-division open space cause it has multiple plausible scales of capitalization. They refine this to sub-division open space because they believe that the cost of purchasing land to provide sub-division space is capitalized into the neighborhood as a whole given that developers pay for the land. They also argue that coarse-scaled fixed effects at the city or county level can potentially identify capitalization of amenities on a large-scale, leaving potential for omitted variable bias in estimates for smaller neighborhood scales. Demographic characteristics such as race, ethnicity, age at the census block group level to are also included to control for potential correlation between the spatial measures of open space provision and socioeconomic background. They further explore the importance of simultaneously accounting for both small-scale and large-scale capitalization by creating measures for MWTP for subdivision open space separated by the spatial extent of capitalization. When comparing the neighborhood-wide MWTP measures, the OLS estimates are small and insignificant whereas the random effects (RE) and Hausman-Taylor (HT) estimates are larger. They also suggest that due to the inability of fixed effects being able to capture the large-scale capitalization, the random effects estimator is able to capture both small-scale and large-scale capitalization with the large-scale willingness to pay being over four times larger than at small scales. Lastly, comparing the RE estimator and HT estimator indicates that the RE estimator underestimates the MWTP by more than 30% and both models show similar proximity-based willingness to pay measures that decrease with distance. They conclude that it is important to account for both large-scale and small-scale capitalization while controlling for potential omitted variable bias.

Although the data for the current study is not panel in nature, Klaiber and Abbott's research provides insight on how fine-scale and coarse-scale fixed effects can influence estimates in hedonic price models which are also applicable to our pooled cross-sectional data. This motivates testing different types of neighborhood fixed effects to capture any omitted variable bias that may be present. We use two types of fine scale fixed effects, Census Tract and PRISM Grid, to define neighborhood level fixed effects in our study. The census tract neighborhoods are on a finer scale than the PRISM Grid, which will allow us to check for robustness of our estimates depending on the specification of our neighborhood fixed effects.

2.3 Subjective Perception of Environmental Amenities

Another environmental amenity that has been commonly explored in hedonic price models is open/green space. In a study conducted by Daams et. al (2016), they attempt to capture the effect of natural space on housing prices for parcels that are close by in the Netherlands. They characterize this by using a survey of perceived attractiveness combined with land use data to measure a buyer's willingness to pay. They assume that natural spaces are capitalized in surrounding property prices and expand work done by Palmquist (2005) by including a measure of the perception of attraction rather than using just land use data. By doing so, they move away from implicit assumptions that buyers evaluate natural spaces with similar land use characteristics as a homogenous good. The baseline specification of the model uses a semi-log function and includes both time and location fixed effects. For the model including locational measures they find that for properties within 0.5km from natural space that is perceived as attractive, there is a 16% price effect which is consistent with previous studies.

Daams et. al (2016) supports empirical literature on subjective evaluations of natural spaces and landscapes by including a measure of perceived attractiveness. They illustrate how subjective perception of environmental amenities are taken into consideration by homeowners when purchasing a house. This parallels with the current study as we attempt to capture the influence of the urban heat island effect on housing prices since the subjective perception of a hotter or cooler day may be absorbed within the selling price. In addition to the time fixed effects (yearly and monthly) that are used in our study, we create measures for the UHI recognizing that weather is observable (a subjective perception) to the buyer during a transaction.

2.4 Estimating Environment Impacts on Housing Price

Estimating the effects of environmental amenities has been explored extensively in hedonic price literature which also lead to the exploration of dis-amenities. The impact of an amenity is considered to be positive on housing prices whereas a dis-amenity would have a negative impact. Some early work conducted by Ridker and Henning (1967) and Keil and McClain (1995) explore different types of environmental dis-amenities such as air pollution or proximity to garbage incinerators, and their impact on housing prices. The literature also coincides with current research on environmental dis-amenities that consider the spatial nature of property data.

A recent study conducted by Montero et. al (2017) explore the effects of air and odor pollution on housing prices in Madrid, Spain with a spatial lens. In order to evaluate the impact of these dis-amenities, they take spatial autocorrelation, spatial heterogeneity, and nonlinearity into consideration for their model specification. By using parametric and semiparametric spatial models, they attempt to capture measured differences in environmental attributes rather than a consumer’s willingness to pay for a perceived environmental dis-amenity in Madrid, Spain. Similar to previous studies, they take a natural log transformation of prices in their data and use the percentage of residents who determine that the neighborhood has serious pollution issues as a subjective environmental factor (Montero et. al 2017). They acknowledge that because of spatial autocorrelation, nonlinearity, and heterogeneity in the data, in some models, residents’ perception of air and odor pollution is insignificant, and these can be addressed with use of spatially lagged terms, areal covariates, and spatial drifts. Overall, impacts of air and odor pollution is significant on housing prices which supports taking environmental dis-amenities into account.

Montero et. al provide evidence that including spatial drifts improves specification strategy when creating measures to test environmental impacts on housing prices. Although we do not use parametric and semi-parametric models for estimation, we consider the spatial characteristics of the weather observations that vary in temperature to construct measures of the UHI across our sample area. Both the spatial and temporal nature of this variable ensures that we have variation in hotter temperatures. By joining the spatial characteristics of the housing data with weather outcomes we can specify the overall influence of the UHI on the housing market. Lastly, we also test weather outcome lags by creating our own spatially lagged temperature variables further adding to the robustness of our estimates.

2.5 Using Spatial Techniques to Characterize Environmental Dis-Amenities

Affuso et. al (2019) illustrate another application of using a spatial autoregressive model to capture the impact of an environmental dis-amenity: noise pollution in metropolitan areas. They determine whether the proximity to an airport influences housing prices in Memphis, Tennessee and find that the recent methods consider the geographical location of housing parcels as a spatial characteristic and utilize multiple approaches such as GIS analyses, contingent valuation, and hedonic models to improve estimates of the directional effects as it takes spatial correlation into consideration (Nelson 2004). The spatial dataset used in the study contains information about the noise levels, property characteristics, and neighborhood characteristics for housing transactions bounded by the urban growth line for Memphis.

Similar to previous studies, they express price in natural log form and include yearly and neighborhood fixed effects, which are derived by merging the data to demographic information at the census tract level. They utilize Esri ArcGIS software to create proximity measures of distance between housing units and closest major road, four major open space areas, and the Mississippi River. In order to estimate the capitalization of airport noise pollution on property values, they employ a traditional hedonic model and borrow from theory of acoustic physics to create a measure of noise pollution. Their results are consistent with previous research that indicates noise pollution is a dis-amenity since an increase in noise pollution is capitalized in the value of properties across the entire sample. However, this varies across the area as different regions have the ability to mitigate the effects of aircraft noise based on other environmental factors.

Affuso et. al find evidence that supports the idea that airport noise is perceived as a negative externality and recognize that their study does not account for potential macroeconomic benefits of the airport. Although some of the bias is mitigated by using proxies for homeowner's propensity of noise avoidance, another limitation of the study that they discuss is the inability to completely tease out the effects of noise produced from takeoffs and landings from other environmental noise. This additional example of a dis-amenity shows justification that environmental impacts can differ depending on use of spatial techniques. We also use urban growth boundary lines to restrict our sample area to Eugene-Springfield and GIS analysis to spatially join our housing parcels to temperature variables for our study. This allows us to test the impact of the UHI measures assigned to each parcel across space and time.

Chapter 3

Climate Change Effects: Urban Heat Island

Economists have shown how environmental amenities and dis-amenities can influence housing prices in cities across the nation and world. A prevalent issue that we face in environmental and natural resources economics is evaluating the economic impacts of climate change. As we experience extreme climate changes, like frequent heat waves, it is not surprising to see that home buyers are cognizant of climate amenities and dis-amenities. The urban heat island effect is an example of an extreme climate outcome and in order to characterize this in our study, we use guidance from existing literature of climate amenities for our model specification.

3.1 Climate Amenities, Climate Change, and American Quality of Life

We can expect that changes in economic welfare can occur from extreme climate outcomes based on where an individual chooses to live. This change is often measured through a quality of life (QOL) index. Previous hedonic studies show that climate preferences for households in the U.S. can vary as estimates of WTP for a unit change in warming temperatures are positive in some studies (Hoch and Drake 1974; Moore 1998), negative in others (Cragg and Kahn 1997, 1999; Kahn 2009; Sinha and Cropper 2013) and close to zero in (Nordhaus 1996) in other studies.

Albouy et. al (2016) explore this in their study as they estimate the dollar value American households place on climate amenities, specifically in temperature. The tradeoff here is that households may suffer from hotter summers but benefit from milder winters (Albouy et. al 2016, pg. 206). Using the foundational framework developed by Rosen (1974) and Roback (1982), they examine how households' willingness to pay (WTP) varies in areas with different climates in the United States. By developing a local QOL index they measure WTP based on living costs of households and their income. One advantage of observing this on a national scale is the geographical and climate variation that is present as some states like California have hot, dry weather while other states like New York have cold, snowy seasonality. Their estimates of amenity values primarily reflect impacts of exposure to climate on comfort, activity, and health, including time use (Graff and Neidell 2012) and mortality risk (Deschênes and Greenstone 2011; Barreca et al. 2015). They implement a hedonic approach since climate amenities have no explicit markets. The underlying intuition for their approach is that households pay higher prices and accept lower wages to live in areas with desirable climate amenities (Albouy et. al 2016, 209). The data to measure QOL was collected from 2,057 Public Use Microdata Areas (PUMA) for 48 states from the 2000 Census which includes wage and housing cost differentials. They implement historical climate data by creating temperature bins of daily average temperatures at the 4km resolution from 1970-1999 and calculate the average numbers of days at each grid point for which the average daily high and low temperature falls within each bin. Some other climate data that they use are monthly precipitation and humidity levels obtained from PRISM and percentage of sunshine on a given day from 156 weather stations in the National Climate Data Center. Lastly, they use predicated climate change data from the Community Climate System Model and control variables for geography and demographics.

In their dataset the average heating degree days is 4.38°F and the average cooling degree days is 1.29°F. They find that households prefer temperatures near 65°F, dislike marginal increases in heat compared to marginal increases in cold and suffer the least from marginal increases in cold or heat once the temperature stabilizes to cold or hot. They also find evidence of heterogeneity in these preferences, with households that are most averse to cold living in the South, consistent with models of both sorting and adaptation (Albouy et. al 2016, 243). When looking at the impacts of climates change, they discover that there is an average welfare loss of 1% to 4% of income per year by 2070-2099 in the predicted climate model assuming business as usual, that is no action is taken to reduce greenhouse gas emissions. These estimates are similar in magnitude to previous studies of economic welfare illustrating that climate impacts require mitigation and the costs can be justified.

The study by Albouy et. al (2016) supports the use of hedonic pricing approach to measure the influence climate change in a cross-sectional setting. They acknowledge that households can mitigate potential damages from climate through adaptation for example, by insulating homes, changing wardrobes, or adopting new activities, which cross-sectional methods account for compared to time series panel approach (Albouy et. al 2016, 207). In our study we will be using similar estimation strategies and climate data as we have pooled cross-sectional data to mitigate the influence of unobservables using neighborhood fixed effects. This also helps with determining mitigation/adaptation methods like upgrading to energy efficient utility systems, that households can implement when the UHI effect is exacerbated.

3.2 Extracting Trade-Off Measures for Physically Coupled Amenities

The QOL index shows that the effects of hotter temperatures on housing prices can cause a loss in economic welfare. The urban heat island provides direct evidence of human activities contributing to a feedback loop that changes ecosystem services by creating localized warming and differences in vegetated landscapes in areas around the urban core (Klaiber et. al 2017, 1053). As this climate change phenomenon affects many more cities across the U.S., there is a focus on studying how individuals adapt to these changes. In a study conducted by Klaiber et. al (2017), they develop a spatial, temporal panel estimator to evaluate how household's value landscape and temperature ecosystem services in Phoenix, AZ. They measure landscaping as a composite index of "greenness" within each parcel and subdivision. The motivation behind this is that they believe that buyers make housing choices based on the joint parcel and subdivision landscapes and its combined effect on the local microclimate caused by the urban heat island effect. They assume that a household's choice of landscaping is driven by the benefits of increased evapotranspiration, shading from trees, shrubs, and grassed areas, and reduction in cooling expenses that alleviate the urban heat island effect (Stone and Norman 2006).

Due to the panel nature of their data they use the Hausman-Taylor model to define the spatial and temporal scale of random effects. Similar to previous studies mentioned, they use census tracts to define neighborhood fixed-effects and interact it with the year of sale to capture the spatial dimension of the random effect and the variations in population density. They normalize the housing prices to 1998 dollars and convert them to an annual rental rate since there was a rapid increase in housing prices during the sample period. The data for the landscape characteristics was gathered from remote sensing data, which covers 12 unique land cover types for the Phoenix area. They use this to measure the percentage of parcels in a subdivision that are green. They also include temperature data at the census tract level obtained from PRISM as they expect that a household's perceptions of micro-climate are relatively coarse so temperature-based sorting will happen at the larger neighborhood level (Klaiber et. al 2017, 1064). Variables for other parcel level GIS attributes such as distance to nearest highway, parks, and downtown Phoenix, were also included in their specification.

The results of the Hausman-Taylor estimate indicate that there is a 0.7% premium for green landscaping at the parcel level, a small but significant effect. At the subdivision level this is much larger; about 12% premium and the interaction effect for green subdivision is significant suggesting that there is a greater capitalization effects for areas with larger parcels. They take advantage of the between/within variation to measure the effect of green landscaping and temperature separately and find that the households are aware of the benefits from landscaping especially, within the local microclimate. They also find evidence that households tend to sort into neighborhoods with lower temperatures and vegetation that mitigate hotter temperatures at both the parcel and subdivision level. Another area that they explore are the aesthetic benefits aside from energy savings that can happen from landscaping choice. They estimate that there is $114 annual capitalization for the mean home of converting from dry to wet landscaping suggesting that there are private benefits from green landscaping.

Although the current study will not be using panel data, Klaiber et. al's (2017) provide insight on specification of fixed-effects and measurement error in hedonic price models. In addition to the two types of neighborhood fixed effects, we include yearly and monthly fixed effects to control for inflation in the housing market and seasonality. We also normalize the transaction prices of homes by converting them to 2014 dollars, which is the last year in our sample period. We can also explore sorting behavior of households across neighborhoods given the climate amenities/dis-amenities for that area.

Chapter 4

Using Weather Observations vs. Climate Outcomes

We have seen in the literature that it is common to use weather measures to identify the causal effects of climate change, especially when there are hotter temperature extremes. Depending on whether those weather measures are historical climate normals or daily temperatures, the choice of using weather versus a climate data to create explanatory variables critically affects the interpretation of the estimated coefficients in the econometric model: that is, whether the outcome is a true climate response or a short-run elasticity of weather (Auffhammer et. al 2013, 181). By distinguishing between weather observations vs. climate outcomes, there is a possibility to tease out the short run and long run effects and economic implications they have for the issue being studied. The temporal and spatial characteristics of temperature variables also add complexity to specification as there may be unobservable variables that are correlated with the weather measure.

4.1 Economic Analyses of Climate Change with Temperature Measures

Auffhammer et. al (2013) delve into the specification of weather observations vs. climate outcomes and common mistakes that are made when using these data. One pitfall they describe when using gridded weather data is that it does not provide enough variation in panel data since each grid takes on an average value across space. They also mention the averaging of daily temperatures can lead to similar issues as the grids are created through interpolation due to some areas having less weather stations than others. This is further exacerbated when fixed effects for time and location are included in a panel setting. They argue that when location fixed effects remove average weather outcomes at the interpolated location, and temporal fixed effects are included, the remaining weather variation is greatly diminished and the variation that is due to stations coming in and out of the sample can potentially account for a significant share of the overall variance (Auffhammer et. al 2013, 187). Another pitfall they present is the correlation of weather variables which causes omitted variable bias. They believe that variables like temperature and precipitation are historically correlated so in order to get unbiased estimates of the effects of these variables both should be included in the model specification. The last pitfall they describe is the spatial correlation of climate variables across space and time. Although weather variation is random across time, they argue that variation across space is less random at refined spatial scales resulting in biased standard errors of estimates. One way they suggest econometricians can combat this is by adjusting for spatial correlation with spatial weights or a nonparametric approach for panel data. Since endogeneity is also a concern with weather data, they suggest looking at how much the underlying station data has changed over time and whether exogenous shocks such as policy interventions influence the frequency of weather data being collected.

Along with the weather data, the researchers look at the integrity of climate prediction models. This is important, as the basis for future predictions occur from the existing global climate data (GCM). The generation of GCM comes from a physics-based model of the global climate in which forecasts of human activities are considered exogenous (Auffhammer et. al 2013, 191). They argue that it is important to quantify and correct aggregation bias that happens at the time and spatial scale when matching the GCM to econometric model. Therefore, they recommend that predicted change in weather should be used in the baseline model rather than using direct GCM output as a future climate measure.

The emphasis of weather specifications illustrated by Auffhammer et. al (2013) show that it is important to consider the underlying issues of historical or future gridded datasets. Depending on the type of data, specifically panel, this can cause bias in estimates of economic impacts of climate change. In order to create measures for the UHI effect for our study we take this into consideration and collect both historical climate data and monthly temperature variables to distinguish between climate outcomes and weather observation. This ensures that our UHI measures are exogenous in our hedonic price model. We will also be using pooled cross-sectional data for our study and GIS analysis to preserve spatial characteristics with two types of neighborhood fixed effects that further control for bias in estimates that may occur from spatial correlation or omitted variables.

4.2 Short Run vs. Long Run Responses to Climate Change

In a recent study conducted by Kolstad and Moore (2020) the estimation of long run climate change effects is further explored with weather observations vs. climate outcomes. The motivation for this comes from concerns that the effect of year-to-year weather variation on economic impacts cannot be used to identify the effect of climate changes because the response to short-run weather fluctuations may be fundamentally different from the response to a permanent change in climate (Kolstad and Moore 2020, 2). They also compare the advantages and dis-advantages of using panel or cross-sectional data in this setting and provide insight on hybrid approaches that will address consequences of using these data types. There is a preference for panel data as it varies both over time and space whereas in cross-sectional data the observations are for one period in time. Early versions of econometric models have used cross-sectional variation in climate to estimate the marginal economic effect of long-run changes in the distribution of temperature and rainfall in the agriculture sector (e.g., Mendelsohn, Nordhaus, and Shaw 1994) however, recent econometric models use panel data to estimate these effects.

The researchers describe the difference between weather and climate as a characteristic of its randomness. This allows for either short run or long run responses from individuals as they learn to adapt their lifestyle. Because weather is inherently random, meaning that at any given point in time (highly predictive) it can be drawn from a probability distribution, the probability distribution over weather outcomes can be thought of as the climate (Kolstad and Moore 2020, 3). This leads to the idea that climate can be perceived from the actual experience of weather, therefore the short-run response to a change in climate can be estimated from the effects of weather fluctuations. They identify that cross-sectional models provide better estimates of long-run responses to climate change because they incorporate the benefits of all adaption methods. In contrast, they believe that linear panel models provide better estimates of short-run impacts of weather since fixed-effects are used to control for unobservables that cross-sectional models do not control for. They suggest the use of hybrid approaches like non-linear panel, multistage, long difference or portioning variation models to estimate response functions at various timescales since omitted variable bias has been a long due concern in the literature.

The parallel of estimating the economic impacts of climate change effects in agriculture to environmental amenities gives us justification to use observed weather data in comparison to historical temperature data as a measure of the urban heat island effect. By relatively comparing hotter to cooler summers we attempt to isolate hot spells which intensify the UHI effect in metro areas while also having enough variation in the weather. The pooled cross-section nature of our data along with yearly, monthly, and PRISM Grid neighborhood fixed effects further provide an advantage in capturing this impact with our UHI measures.

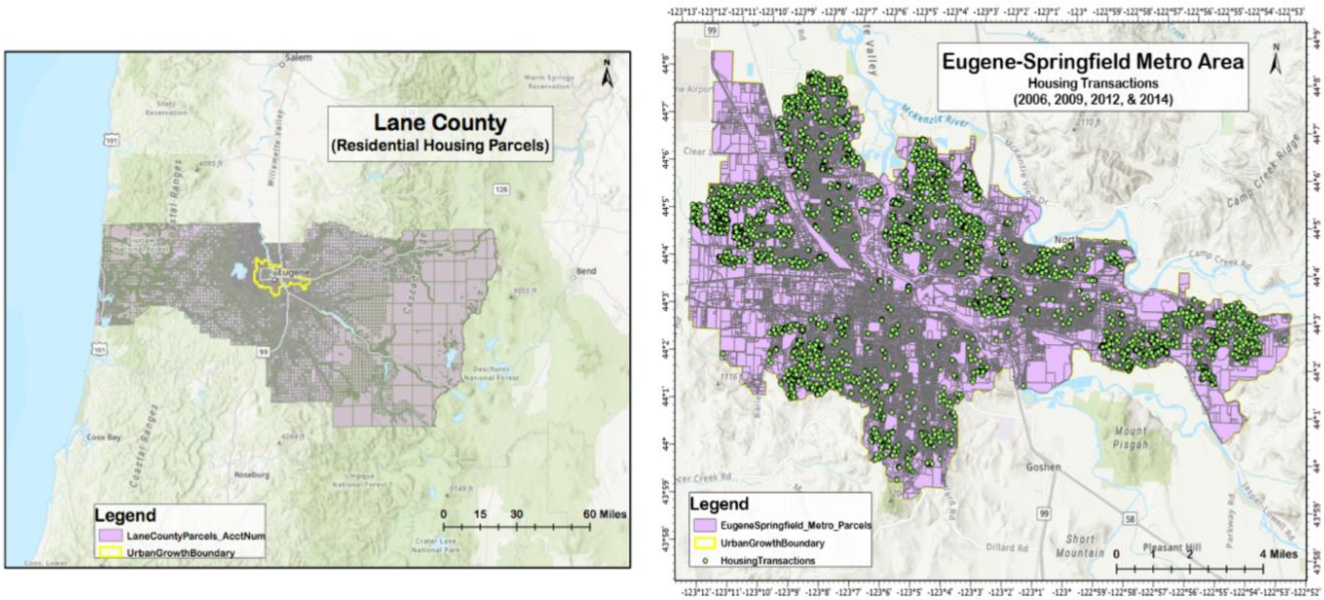
Chapter 5

Study Area

The Eugene-Springfield area is located within Lane County in the eastern region of Oregon near the confluence of the Willamette and Mackenzie Rivers. The study area covered 155.52 km^2 with latitudinal range of 43°58′ N to 44°8′ N and longitudinal range of -123°12′ W to -122°52′ W (Figure 1). This is the third largest metropolitan area in Oregon with a total population of 234,224 people. In recent years, the population has grown 5.5 % with median home value of $272,000 (U.S. Census Bureau 2018). It is a college town home to the University of Oregon, Northwest Christian University, and Lane Community College making it a cultural hub. Due to this characteristic, many residents of this metro are usually students, faculty, and staff of these institutions. This demographic includes both renters and owners, however for this study we focus on transactions of single-residence homes. The state of Oregon has a special land use program that protects farm and forest land, therefore cities and counties plan for population growth using compact development principles defined by urban growth boundaries (City of Eugene 2017). These boundaries include city limits and additional land that can be developed into homes, jobs, parks, and schools to accommodate 20 years of population growth. In order to create a measure for the urban heat island effect, spatial variation in housing parcels and in temperature effects from hot spells is necessary. Further, best practices in hedonic estimation is to limit analysis to a single competitive land market. Thus, the study area is restricted by the Eugene and Springfield urban growth boundaries.

The climate in the Willamette Valley—which contains Eugene and Springfield—is cool and moist with over 170 different crop and livestock items being produced in the area. Its fertile soil makes it an ideal environment to grow timber, hazelnuts, grass and legume seeds (USDA 2019). The seasonal variation in weather ranges from abundant precipitation in winter and spring seasons and hot, dry weather in the summer making it prone to extreme wildfires (NOAA 1997).

Figure 1: Location Map of Lane County (left) and the Eugene-Springfield Metropolitan Area (right)

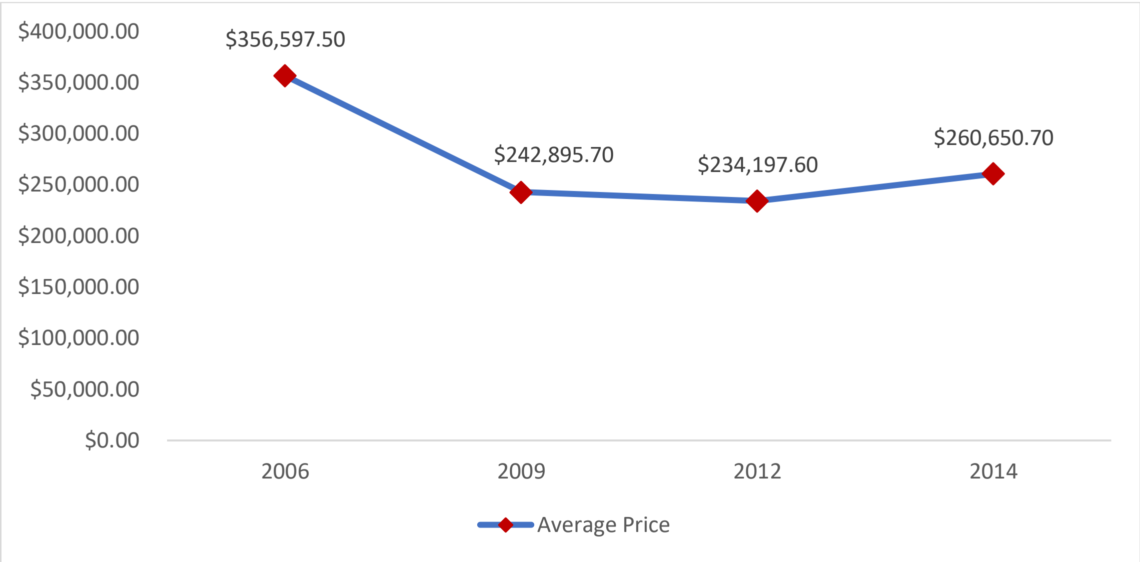


Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community, Sources: Esri, HERE, Garmin, FAO, NOAA, USGS, © OpenStreetMap contributors, and the GIS User Community

5.1 Housing Transactions Data

The data for housing transactions in Lane County was purchased from CoreLogic's University Data Portal, which includes deed records and tax assessor data from 2004 to 2015. To select the sample used to estimate our hedonic price model, we focused on transactions that occurred in the Eugene-Springfield metropolitan area between May and September. Since the urban heat island effect occurs during the hottest time of the year, we focus on summer transactions with buffer months, May and September, as it is typical for closing date to occur within a few weeks to a month after an offer is accepted. The assessor data includes the sale amount (*price*) and household characteristics of 3,309 single-residence parcels which are uniquely identified by the account number (*acctnum*), shown in Table 1. All transaction prices are adjusted to 2014 dollars using the House Price Index from the Federal Housing Agency. Zero-dollar transactions were removed from the sample and the market improvement value (*ImpValue*), which is provided by the local taxing/assessment authority, is used to capture the value of the physical structure and housing characteristics. Figure 2 below shows the change in average price of a parcel in our sample over time, which ranges from $234,197.60 to $356,597.50. The fluctuations in the average price reflect the housing market crash that occurred during our sample period and we control for this using yearly fixed effects, which are further discussed in the identification strategy.

Figure 2: Average Price of a House Sold in 2006, 2009, 2012, and 2014



The variable *acres* represents the total acreage of a parcel. Also included are two types of neighborhood fixed effects using census block groups (*Census Tract*) and the PRISM Grid; *Census Tract* is categorical variable that represents the census tract ID name as it is a string data type. The parcels fall within 37 unique census tracts and 20 unique PRISM Grids, we discuss how these fixed effects are also specified later in the identification strategy. The sale year (*SaleYear*) and sale month (*month*) have been coded as dichotomous variables to control for inflation in prices and any seasonal effects. The overall dataset includes 3,532 transactions, this is higher than the number of unique parcels as some homes have sold multiple times over the years.

Table 1: Descriptive Statistics of Housing Transactions

Variable	Observations	Mean	Std. Dev.	Min	Max
acctnum	3532	-	-	-	-
ImpValue	3532	198658.36	96198.546	19721	1387106

acres	3532	.178	.161	0	3.65
SaleYear	3532	2009.498	3.218	2006	2014
month	3532	6.946	1.41	5	9
day	3532	17.101	8.772	1	31
price	3532	288142.51	749722.11	10456.412	19726054
year1	3532	.388	.487	0	1
year2	3532	.201	.401	0	1
year3	3532	.199	.399	0	1
lnp	3532	12.347	.534	9.255	16.797
tractid	3532	-	-	-	-

*Year1, 1 if the sale year is 2006

*Year2, 1 if the sale year is 2009

*Year3, 1 if the sale year is 2012

*lnp is a natural log transformation of price

*tractid represents the census block group assigned to a neighborhood by the U.S. Census Bureau

5.2 Climate and Weather Data

The data for the summer climate (long run measure) and weather (short run measure) of the Eugene-Springfield area was collected from the PRISM Climate Group. In studying the impact of climate on agriculture, health, and electricity usage, temperature has been measured by the number of days in various temperature bins (Schlenker and Roberts, 2009; Deschenes and Greenstone, 2011; Albouy et al., 2016). Table 2 shows the descriptive statistics for the following monthly weather data collected for each 4km grid covering the study area: maximum temperature (*tmax*), mean temperature (*tmean*), and the geographical variables, elevation, latitude, and longitude. Historical climate normals, calculated from monthly 30-year "normal" temperature covering the conterminous US, averaged over the period 1981- 2010, were also included (*LRtmin, LRtmax,* and *LRtmean*,).

Table 2: Descriptive Statistics of Climate and Weather Data

Variable	Observations	Mean	Std. Dev.	Min	Max
PRISM Grid	3532	-	-	-	-
Elevation (ft)	3532	543.52	208.061	374	1040

SeasonYear	3532	-	-	-	-
SeasonMonth	3532	6.946	1.41	5	9
tmean (°F)	3532	62.975	4.833	53.2	70.9
tmax (°F)	3532	77.266	6.462	64.4	87.3
max_lag (°F)	3532	77.31	6.357	64.4	87.3
avg_lag (°F)	3532	62.947	4.775	53.2	70.9
LRtmean (°F)	3532	61.924	4.32	54.5	66.7
LRtmax (°F)	3532	75.618	5.841	65.9	82.4
LRmax_lag (°F)	3532	72.85	7.657	62.7	82.4
LRavg_lag (°F)	3532	59.936	5.771	52.3	66.7
temp_dev (°F)	3532	14.291	2.063	10.9	17.4
LR_tempdev (°F)	3532	13.694	1.604	11.3	15.8
avg_tempdev (°F)	3532	1.051	1.586	-2.4	4.3
max_tempdev (°F)	3532	1.648	1.949	-3.7	5.1
avg_tempdev_lag (°F)	3532	3.011	4.189	-2.4	12.9
max_tempdev_lag (°F)	3532	4.46	6.115	-3.7	17.7

*All temperatures data were collected for on monthly basis

*Avg_tempdev_lag is the previous month's average temperature assigned to a parcel based on sale month

*Max_tempdev_lag is the previous month's maximum temperature assigned to a parcel based on sale month

*SeasonMonth & SeasonYear represent the month and year that the seasonal climate data was collected for

The historical normals dataset describes the average monthly and annual conditions for the recent three decades, giving us insight to the spatial variation in the climate in the U.S. (PRISM 2019). The advantage of using mean summer temperatures is that they capture seasonality, which annual heating and cooling degree days and temperature bins do not (Sinha et. al 2017). The average normal temperature ranges from 54.5-66.7°F and maximum normal temperature ranges from 65.9-82.4°F for our sample area, Eugene-Springfield. We focus on the hottest summers on record for the area, 2009 & 2014, along with cooler summers, 2006 & 2012, to ensure that we have variation in our key independent variable, the urban heat island (UHI) effect. We difference out the normal temperature for a month from the observed maximum temperature for the month (*tmax-tmean*) to gauge if the summer season was particularly hot or cool relative to the normal. Identifying hotter summers help with identifying the UHI effect as the frequency of hotter temperatures creates a core of heat in urban areas (Kenward et. al 2014). The scope of our data allows us to clearly identify the variation in the weather which assists in specifying the UHI effect spatially and temporally.

Chapter 6

Econometric Framework

The specification of our model starts with a traditional linear regression model estimated with OLS, a common approach in hedonic price models. Given the pooled cross-section nature of the data we adjust for the presence of heteroskedasticity using robust standard errors and include a time dummy variable to capture structural changes over time. The advantage of the time dummy is that it allows the intercept to have a different value in each period of our sample. A common functional form that is often used in hedonic price models is a log-linear form which narrows the range of the transformed variable and ensures that our model is less sensitive to extreme values (Kuminoff et. al 2010; Riera et. al 2006; Klaiber et. al 2017; Ozbakan and Kale 2012). Taking a natural log transformation of our dependent variable, *price*, results in the equation:

$$lnP_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Temp_{it} + Year_t + Month_{m(i)} + Neighborhood_{N(i)} + \varepsilon_{it} \quad [2]$$

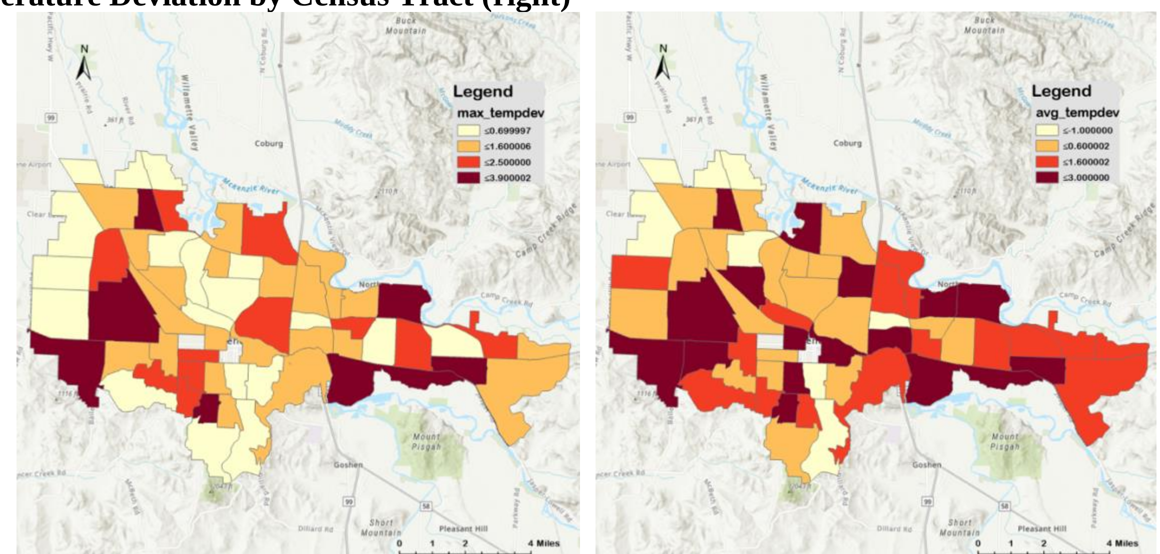
where lnP_{it} represents the log price of a house *i* at a given time *t*, X_{it} represents a vector of housing variables (*log of ImpValue* and *acres*), $Temp_{it}$ represents a vector of urban heat island variables (*avg_tempdev, max_tempdev, avg_tempdev_lag,* and *max_tempdev_lag*), $Year_t$ is a dummy variable of the year a housing transaction was made, $Month_{m(i)}$ represents monthly fixed effects, $Neighborhood_{N(i)}$ represents the neighborhood fixed effects indexed by N for the different specifications (*Census Tract* and *PRISM Grid*), and ε is the error term. We also estimate the following linear model for robustness checks:

$$P_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Temp_{it} + Year_t + Month_{m(i)} + Neighborhood_{N(i)} + \varepsilon_{it} \quad [3]$$

6.1 Identification Strategy: Measurement of $\boldsymbol{Temp_{it}}$

The urban heat island effect is captured in our model by taking the difference between maximum monthly temperature for the month that the house is sold (*tmax*) and maximum normal temperature for the same month (*LRtmax*) to observe the temperature deviation within a given month from the historical normal. The maximum temperature deviation (*max_tempdev*) varies from 0°F to 3.8°F in 2006, -0.5°F to 4.3°F in 2009, -3.7°F to 3°F in 2012, and -0.1°F to 5°F in 2014. Similarly, another measure created to capture and test this effect is the difference between average monthly temperature for the month that the house is sold (*tmean*) and average normal temperature for the same month (*LRtmean*) represented by the variable *avg_tempdev*. The average temperature deviation (*avg_tempdev*) varies from -1.3°F to 2.5°F in 2006, -0.3°F to 3°F in 2009, -2.4°F to 1.6°F in 2012, and -0.2°F to 4.3°F in 2014. The left panel on Figure 3 below, shows the spatial variation in the overall maximum temperature deviation by neighborhoods defined by *Census Tract*.

Figure 3: Maximum Temperature Deviation by Census Tract (left) and Average Temperature Deviation by Census Tract (right)



The temperature deviation measures, *max_tempdev* and avg*_tempdev*, help identify the urban heat island effect because we are using weather observations at monthly and yearly time scales. This parallels specification strategies used within agricultural economics and recreational fishing demand studies, as temperature is assumed to be exogenous in the presence of controls for spatial factors (e.g. neighborhoods, regions) and temporal factors (e.g. time dummies) (Blanc and Schlenker 2017; Schlenker and Roberts 2009; Dundas and H. von Haefen 2020). As mentioned by Kolstad et. al (2020), the random nature of weather cannot be controlled by the economic agent and is generally unanticipated, while production choices (e.g., what to plant and when, or how much capital to invest) are decisions made by the economic agent and are based on factors such as prices and expectations about (stochastic) weather. We assume that these temperature deviations are caused by the urban heat island effect since it intensifies the heat in areas with a higher density of buildings, industrial areas, and major highways/roads. This indicates that the natural within variation in weather variables (*max_tempdev* and *avg_tempdev)* is essential in generating a plausibly exogenous variable that helps identify the urban heat island effect and reduce bias caused from any unobservable factors in our models which are also unlikely to be correlated with random weather deviations.

6.2 Timing Issues with the Urban Heat Island Measures

It is expected that the timing between when the house price is negotiated to the closing date of a transaction can vary from a few weeks to a month in the real estate market. Since the weather is observable and known to the buyer during the initial phase of the home buying process when price is being negotiated, we can expect that the weather from this time can influence the value of a home. This perception in weather outcome can create a lag in the influence of the weather effect on housing prices because the actual closing date of the home can occur much later in time. Therefore, we create alternative measures of one-month lagged temperature deviation (*max_tempdev_lag* and *avg_tempdev_lag*) by assigning the previous month's weather to a housing transaction (Montero et. al 2017). Re-estimating the econometric model with alternative lagged temperature deviations is meant to check for robustness in the estimate. Aligning with best practices in hedonic property value models, the choice of the amenity variable (urban heat island measures), the source of exogenous variation in the amenity (randomness of weather observations), and the composition of our sample (removing zero-dollar transactions and including repeated sales of a parcel) contribute to the robustness of our estimates (Bishop et. al 2019, 17).

6.3 Measurement of Cooling Capabilities ($Temp_{it}$*top25*)

We hypothesize that the cooling capabilities or energy efficiency of a home can influence its price however, due to data limitations we cannot explicitly control for whether a parcel has air conditioning or not. We attempt to control for this by creating an interaction term that picks up high-value housing structures that are likely to have air conditioning systems that provide adaptation to hot spells. First, we create a dummy variable, *top25*, that indicates whether or not a parcel falls within the top quartile of market improvement values then interact with our UHI measures, *avg_tempdev, max_tempdev, avg_tempdev_lag,* and *max_tempdev_lag*. We test this interaction term in all of our models which allows us to differentiate the UHI effect across wealthy and less wealthy neighborhoods and determine whether homes with higher physical quality (as measured by market improvement value) are less susceptible to hot spells in property transactions.

6.4 Measurement of X_{it}

The parcel specific variables in our model are represented by *ImpValue* and *acres*. Under the assessed value method, all of the variables of the structural housing attributes are theoretically compiled into one statistic – the assessment (Esquire 2008), therefore it is common practice to use the assessed structural value on the right-hand side of hedonic price models. The values of characteristics associated with a property's housing structure, such as the number of bedrooms, bathrooms, garage, fireplace, and landscaping are lumped into this assessed structural value (Horsch and Lewis 2009). We use the market improvement value, *ImpValue* in our specification, following the logic that all attributes of the physical housing structure would be capitalized into the home's improvement value. This specification is consistent with property assessments, whereby a property's value is the linear sum of its improvement value and its land value. A coefficient is multiplied by *ImpValue* to capture any systematic under or over-assessments made by assessors relative to that observed in market transactions. In simple specifications with P_{it} represented as a linear rather than log-transformed variable, we fail to reject the null hypothesis that the parameter on *ImpValue* is equal to one (5% level). Thus, assessments of *ImpValue* appear to accurately reflect the market. The literature also does not provide concrete guidance on the selection of variables or functional form in hedonic models for individual housing attributes, therefore we avoid misspecification and introducing bias in our model by using the market improvement value (Horsch and Lewis 2009).

Figure 4: The Average Market Improvement Value of Parcels by Neighborhood

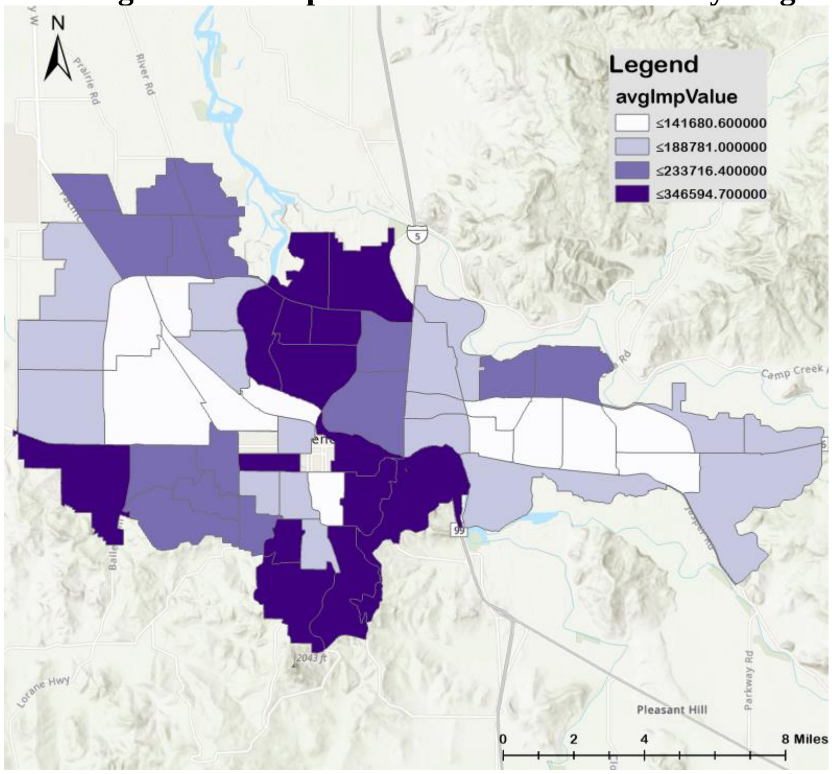


Figure 4 shows the variation in the market improvement value of parcels within the Eugene-Springfield by census block. The dark purple areas represent parcels that have average market improvement value less than \$346,594.70 and the white areas represent parcels that have average market improvement value less than \$141,680.60, demonstrating substantial spatial variation in market improvement value. The parcels with the highest market improvement value (dark to light purple) indicate the neighborhoods with the most expensive housing structures. Additionally, we also expect that the size of a parcel (*acres*) positively contributes to the value of a home given that larger parcels sell for a higher price. The combination of these parcel-specific variables address observable heterogeneity among housing parcels in the Eugene-Springfield area, strengthening our model specification.

6.5 Measurement of $Year_t$

We implement a dummy for the year of sale to capture unobserved dynamic economic processes that could affect the housing price and other unobserved neighborhood heterogeneities

(Caudill, Affuso, and Yang 2015). As shown in Figure 2 earlier, there is a large drop in housing prices from 2006-2008, about $113,702, that was caused by the U.S. housing market crash which occurred during the financial crisis of 2008. The advantage of using the year dummy variable is that it controls for this exogenous shock in housing prices that were widely acknowledge as leading to the Great Recession.

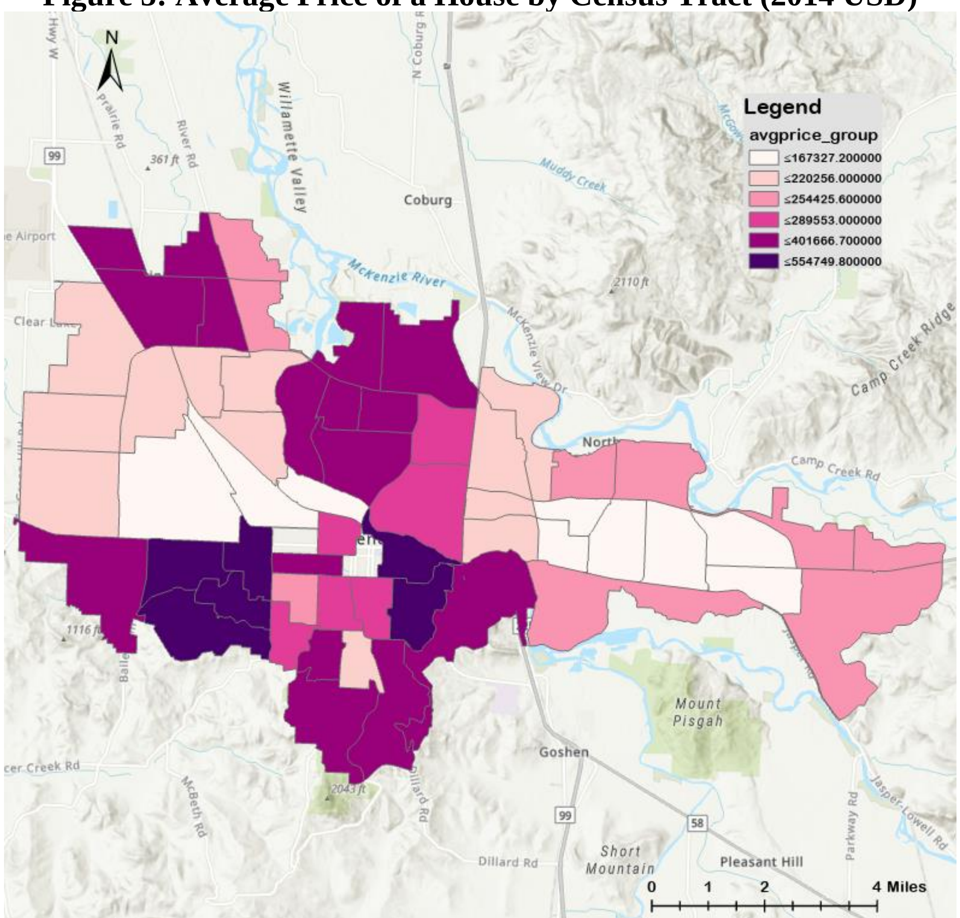
6.6 Measurement of $\boldsymbol{Month_{m(i)}}$

Another concern with a hedonic price model is that seasonality effects can often be correlated with both the dependent variable and independent variables in a model. For example, in the real estate market, summer is the busiest time of year which impacts the number of, and potentially the quality of housing transactions that occur. An increase in the amount of sales may occur during seasons when sellers of homes expect to have more potential buyers. To control for this seasonality, we implement monthly fixed effects which help isolate the causal relationship between the price of a house and the urban heat island variables, by separately accounting for the seasonal impacts of summer sales.

6.7 Measurement of $\boldsymbol{Neighborhood_{N(i)}}$

We adjust our specification above to include two types of neighborhood fixed effects. Since the definition of neighborhood is arbitrary, we present estimates based on the census block groups and the PRISM Grid used to define neighborhood fixed effects. The neighborhood fixed effect measures control for unobserved neighborhood amenities and dis-amenities, including the demographic composition of neighborhoods such as income, race, etc. contained in the census block groups. Adding these neighborhood fixed effects also explicitly controls for local amenities such as parks, recreation spaces, and proximity to urban center, that influence the price of a house. Figure 5 shows the variation in the average price of a home based on the census block groups showing wealthy and less wealthy neighborhoods in our sample. Klaiber and Abbott (2011) mention that coarse scale fixed effects (city or county) leave the potential for bias due to omitted variables for smaller neighborhood scales but with the use of two types of fine scale fixed effects (neighborhoods) we address this concern in our model as our parcels fall within 37 unique *Census Tracts* and 20 unique *PRISM Grids* ensuring that we have variation within our fine scale fixed effects. The neighborhood fixed effects help capture the effect of climate on housing prices, and so this study relies on within-neighborhood variation in temperature across the cooler summers (2006, 2012) and hotter summers (2009, 2014) in our sample to identify the urban heat island effect. The intention of the neighborhood fixed effects is to absorb the price effect of spatially clustered omitted variables ensuring that our measures of observed temperature deviations are quasi-random and provide adequate within variation needed to identify the influence of the urban heat island effect on housing prices (Kuminoff et. al 2010).

Figure 5: Average Price of a House by Census Tract (2014 USD)

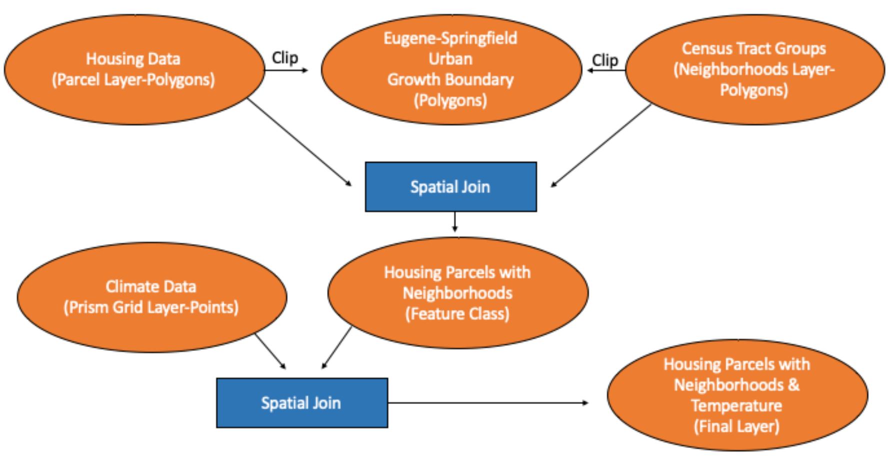


Chapter 7

Measuring Spatial Data with Geographic Information Systems (GIS)

Recent literature has emphasized that omitted variable bias is a major issue in hedonic price models when parcel level amenities and dis-amenities are not observed in spatial datasets. While the geographic scale may impact the magnitude of the estimated effects, there is consistent evidence that these spatially heterogeneous amenities are correlated with landscape and temperature variables, however with the use of GIS software it has become easier to control for spatial amenities (Klaiber et. al 2017). We combine the housing and climate data with Esri ArcGIS Pro so that we can assign temperature variables to each housing parcel in the sample. Figure 6 shows a workflow of how this was executed. Each parcel was connected to the GIS parcel data by account number assigned by the assessor, then clipped to the Eugene-Springfield urban growth boundary line. We then define neighborhoods using census tract groups and overlay that with the housing parcels layer. Using the spatial join tool, we link housing parcels to census tract groups so that each parcel is associated with its neighborhood fixed effects. The spatial join tool allows us to preserve all spatial characteristics associated with the parcels. Then a feature class was created using the latitude and longitude associated with each PRISM grid that contains the climate data. Each neighborhood was then connected to the PRISM grid using a spatial join in GIS to spatially connect a housing parcel to temperature variables.

Figure 6: GIS Workflow shows Sequence of Operations



7.1 Summary of Identification Strategy and Empirical Approach

GIS analysis of spatial data facilitates our econometric identification strategy and allows us to maintain the integrity of the spatial characteristics of the housing and climate data in our sample. Using the two types of neighborhood fixed-effects, parcel-specific variables, and controlling for time trends and seasonality strengthen our specification strategy for isolating the influence of the urban heat island effect on home prices. The mean independence assumption in the classic linear regression model requires that E$[\varepsilon_{it} \big| X_{it}, Temp_{it}, Year_t, UHI * top25_i, Month_{m(i)}, Neighborhood_{N(i)}\big] = 0$. Since omitted variable bias caused by other unobservables of housing and neighborhood amenities is a common concern in hedonic model, we rely heavily on the random nature of weather and its spatial and temporal variation to create exogenous temperature measures of the UHI effect. This ensures that all of our time-varying structural components are uncorrelated with the error term reducing bias and adding to the consistency of our estimates given the pooled-cross sectional nature of our data.

Chapter 8

Empirical Results for Model with Logged Dependent Variable

A common hedonic specification is to take a log transform of the transactions price (the dependent variable) and the market improvement value (an independent variable). Table 3 and 4 contain all models with price in log form so the estimated coefficients can be easily interpreted as a percent change. The overall model fit is measured by adjusted R^2 is around 0.49. One notable feature of our model is the use of market improvement value in place of separate variables indicating physical structure (e.g. number of bedrooms, garage, etc.). However, the adjusted R^2 measure of goodness-of-fit is comparable to other similar hedonic models that separately include physical attributes of the house, such as Dundas and Lewis (2020). The estimates of our model indicate that there is a significant relationship between the price of a house and the average lag temperature deviation and maximum lag temperature deviation variables in Table 3 and 4. Robust standard errors are used to correct for any violation of the assumption that the variance of the error terms is constant for the estimated parameters.

All models include time dummies for the year of house sale (closing date) and monthly fixed effects. The neighborhood fixed effects are included in the specification to control for any unobserved neighborhood qualities represented by the *PRISM Grid* and *Census Tract* variables. Also included in each model are the acres of a parcel, the log transformation of the market improvement value, which captures the value of the structure only (this includes housing characteristics such as the number of bedrooms, number of bathrooms, whether there is a fireplace, backyard, pool, etc.), a measure of the UHI, an interaction term between the UHI measure and whether the parcel falls within the top quartile of market improvement value in our sample, and a lag temperature variable.

In Table 3 and 4, the estimated coefficient of the variable acres has a positive but statistically insignificant effect on the price. The coefficient of the time dummies for year of sale are all statistically significant and show that homes sold in 2006 sell for 22-24% more compared to homes sold in 2012. The estimates of the market improvement value are positive as expected across all models and show that a 1% change in the improvement value of the structural components of a home would approximately increase the housing price by 0.70-0.73%. For example, if a house’s total value is \$300,000, and its market improvement value is \$200,000 (these numbers are close to our sample means), a 1% change in improvement value would raise improvement value by $2000, and therefore change total value to $302,000, which works out to an approximate 0.67% change. So, the range of 0.70%-0.73% in the estimates are very reasonable for our model. We control for seasonal effects by implementing monthly fixed effects, which are positive and statistically significant if a house is sold in July in model 1, 2, 3, and 4. The estimates of the coefficient for houses sold in June and August are negative and statistically insignificant in all the models.

Table 3: Four Estimated Hedonic Price Models including Maximum Temperature Deviation

With natural log transformation of price and market improvement value (ImpValue)

	(1)	(2)	(3)	(4)
max_tempdev	0.000889		-0.000962	
	(0.00500)		(0.00494)	
max_tempdev_lag	-0.00897*	-0.00917*	-0.00996**	-0.0101**
	(0.00493)	(0.00493)	(0.00504)	(0.00503)
max_tempdev*top25	0.0161**		0.0151**	
	(0.00655)		(0.00662)	
max_tempdev_lag* top25	-0.00411*	-0.00255	-0.00502**	-0.00359
	(0.00249)	(0.00232)	(0.00251)	(0.00235)
acres	0.00313	0.00434	0.00860	0.0108
	(0.0493)	(0.0485)	(0.0508)	(0.0511)
ImpValue	0.722***	0.736***	0.701***	0.714***
	(0.0226)	(0.0221)	(0.0227)	(0.0223)
Year Time Dummy	Included	Included	Included	Included
Monthly Fixed Effects	Included	Included	Included	Included
Neighborhood Fixed Effects	PRISM Grid	PRISM Grid	Census Tract	Census Tract
Constant	3.794***	3.628***	4.226***	4.092***
	(0.296)	(0.290)	(0.292)	(0.288)
Observations	3532	3532	3532	3532

R^2	0.496	0.495	0.499	0.498
Adjusted R^2	0.491	0.491	0.492	0.491

Standard errors in parentheses

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

Our measures of the UHI, *max_tempdev_lag* and *avg_tempdev_lag*, indicate that there is a negative influence on housing prices from hot spells that occur a month prior to the sale. The estimates from model 4, suggest that a one degree increase in maximum lag temperature deviation causes an approximate 1% decrease in housing prices for those homes below the top quartile in improvement value, indicating that the weather observed in a previous month can influence housing prices for the less expensive physical structures. In Table 3 and 4, the estimates in model 4 give very similar results which differ when we use the maximum temperature deviation or average temperature deviation in our specification. With the interaction term, we find some evidence that the UHI has a much smaller negative effect on home prices for the top 25% of improvement values, but the evidence is somewhat weak and varies across model specifications. For model 1 and 3 this indicates that a one degree increase in the UHI has a larger positive effect on home prices (by 1.5%-1.6%) for homes that fall within the top quartile of market improvement values compared with homes that fall below the top quartile of market improvement values (Table 3).

Table 4: Four Estimated Hedonic Price Models including Average Temperature Deviation
With natural log transformation of price and market improvement value (ImpValue)

	(1)	(2)	(3)	(4)
avg_tempdev	-0.00681		-0.00592	
	(0.00562)		(0.00559)	
avg_tempdev_lag	-0.00804	-0.00846	-0.00989*	-0.0103*
	(0.00584)	(0.00583)	(0.00585)	(0.00584)
avg_tempdev* top25	0.0179**		0.0163*	
	(0.00909)		(0.00915)	
avg_tempdevlag* top25	-0.00369	-0.00228	-0.00497	-0.00372

	(0.00349)	(0.00326)	(0.00353)	(0.00330)
acres	0.00434	0.00705	0.0104	0.0123
	(0.0485)	(0.0492)	(0.0500)	(0.0507)
ImpValue	0.722***	0.732***	0.702***	0.711***
	(0.0237)	(0.0224)	(0.0237)	(0.0225)
Year Time Dummy	Included	Included	Included	Included
Monthly Fixed Effects	Included	Included	Included	Included
Neighborhood Fixed Effects	PRISM Grid	PRISM Grid	Census Tract	Census Tract
Constant	3.741***	3.609***	4.165***	4.061***
	(0.297)	(0.284)	(0.290)	(0.279)
Observations	3532	3532	3532	3532
R^2	0.495	0.495	0.498	0.498
Adjusted R^2	0.491	0.490	0.491	0.491

Standard errors in parentheses

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

8.1 Robustness Check with Level-Level Model

As a robustness check, we re-estimate the UHI effect in models where all prices (transaction price and market improvement value) are expressed in linear rather than logged form. This type of model is commonly referred to as a level-level model. The linear level-level models, shown in Table 5 & 6, indicate that there is a significant relationship between the price of a house and the average temperature deviation and maximum temperature deviation variables. Both tables contain a temperature lag variable which takes the previous month's weather into account when making a house sale represented by the average lag temperature deviation and maximum lag temperature deviation variables. For example, if a house sale occurred in the month of June, the previous month's weather deviation, May was assigned to the transaction. Model 3 in Table 5 shows that the price of a house sold in 2006 is expected to be $134,848.60 higher than those sold in 2009, 2012, and 2014. Contrastingly, the price of a house sold in 2012 is expected to be $92,127.90 less than those sold in 2006, 2009, and 2014. The estimates of the time dummies are similar in magnitude and statistical significance to our initial OLS models showing consistency in the decline of housing prices. The coefficients of the market improvement value remain positive and have a statistically significant effect on the price of a house in all models. When looking at the estimated coefficients of homes sold in August, we find that they are positive and statistically significant in all models while the other monthly fixed effects are insignificant in the lagged models. Table 5 also shows that the estimated coefficients of maximum temperature deviation are negative and statistically significant in models 1 and 3. We find that if the maximum temperature deviation increases by one degree the price of a house is expected to decrease by $18,858.60 in model 1. Results in model 3 which shows that if the maximum temperature deviation increases by one degree the price of a house is expected to decrease by $17,666. This estimate is similar in magnitude to the estimated maximum temperature deviation coefficients in the initial regressions, which suggest consistency in our estimates.

Table 5: Four Estimated Hedonic Price Models with Maximum Temperature Deviation including Temperature Lags

All models are estimated by samples corrected for heteroskedasticity

	(1)	(2)	(3)	(4)
max_tempdev	-18858.6**		-17666.0**	
	(8570.8)		(8171.6)	
max_tempdev_lag	4191.4	4087.9	9012.0	8863.0
	(4780.1)	(4785.5)	(6748.3)	(6729.0)
max_tempdev*top25	3060.0			
	(5323.1)			
max_tempdev_lag*top25	1546.9	1678.8	7422.7	1527.2
	(2218.8)	(1845.8)	(4527.7)	(1937.7)
acres	-134134.7**		-173089.2**	-176144.2**
	(63934.4)		(83441.0)	(85285.9)
Improvement Value	1.194***		1.005***	1.046***
	(0.143)		(0.135)	(0.121)
Year Time Dummy	Included	Included	Included	Included

Monthly Fixed Effects	Included	Included	Included	Included
Neighborhood Fixed Effects	PRISM Grid	PRISM Grid	Census Tract	Census Tract
Constant	18528.5	-43856.1	117349.6	60697.1
	(97016.7)	(117546.6)	(120786.9)	(134491.6)
Observations	3532	3532	3532	3532
R^2	0.074	0.073	0.050	0.049
Adjusted R^2	0.065	0.065	0.036	0.036

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The estimated coefficients in Table 6, show that the average temperature deviation are also negative and has a statistically significant effect on the price of a house in model 1 and 3. We find that if the average temperature deviation increases by one degree, the price of a house is expected to decrease by $28,875.10 in model 1. Results in model 3, show that if the average temperature deviation increases by one degree, the price of a house is expected to decrease by $28,096.20. The estimated coefficients vary slightly in magnitude in the models depending on the type of neighborhood fixed effects used, adding to the robustness of our estimates. The coefficients of the average lag temperature deviation, maximum lag temperature deviation, and interaction term are positive but statistically insignificant, in all models that they are included in both Table 5 and 6.

Table 6: Four Estimated Hedonic Price Models with Average Temperature Deviation including Temperature Lags
All models are estimated by samples corrected for heteroskedasticity

	(1)	(2)	(3)	(4)
avg_tempdev	-28875.1**		-28096.2**	
	(12994.6)		(13080.7)	
avg_tempdev_lag	5477.5	5468.1	4167.3	3410.7
	(6233.8)	(6469.3)	(5720.2)	(5471.8)
avg_tempdev*top25	-19429.9	-32241.5	-16840.9	

	(21476.2)	(21834.9)	(21513.1)	
avg_tempdev_lag*top25	3595.7		3122.8	1282.4
	(3799.3)		(3858.1)	(2355.7)
acres	-129362.3**	-136212.5**	-170000.9**	-177159.1**
	(63529.7)	(66062.3)	(82802.9)	(86371.0)
Improvement Value	1.261***	1.358***	1.080***	1.053***
	(0.185)	(0.223)	(0.175)	(0.126)
Year Time Dummy	Included	Included	Included	Included
Monthly Fixed Effects	Included	Included	Included	Included
Neighborhood Fixed Effects	PRISM Grid	PRISM Grid	Census Tract	Census Tract
Constant	20980.0	-40424.5	269152.7**	182092.0
	(93500.6)	(114613.6)	(112724.1)	(115166.1)
Observations	3532	3532	3532	3532
R^2	0.076	0.074	0.051	0.049
Adjusted R^2	0.067	0.066	0.038	0.036

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8.2 Summary of Results

Our results indicate that the overall UHI effect has a negative influence on housing prices. We have weak evidence that the negative price effect of the UHI is larger for those homes which have less expensive physical structures (the bottom 3 quartiles of market improvement value), and that the UHI has an insignificant effect on the price of the homes with the most expensive physical structures (the top quartile of market improvement value). However, the evidence is stronger for an overall average negative UHI effect on prices than the evidence on the heterogeneity of the UHI effect across homes with different physical structure values. Given the different functional forms tested in our OLS models, we find that the independent variables explain far more of the variation in the log transformed prices than for linear representations of prices. The log form is also preferred because our dependent variable is a positive price, and the log transformation narrows the range of the dependent variable which makes OLS estimates less sensitive to extremely large values (Wooldridge 1960, 181). Exploring two alternative types of neighborhood fixed effects further controls for omitted neighborhood amenities and dis-amenities and are important in reducing omitted variable bias. Since the census tract fixed effects also control for demographics in our sample, we prefer this compared to the PRISM Grid fixed effects although the estimates vary slightly in magnitude.

Chapter 9

Conclusion

The estimates of our hedonic price model indicate that housing prices are overall negatively influenced by the urban heat island effect. The UHI measures, maximum lag temperature deviation and average lag temperature deviation, are significant and negative in the log-linear models indicating that the UHI effect in the previous month influences housing prices since the weather is observed by the buyer during the initial transaction. Our results illustrate that the overall UHI effect acts as a climate dis-amenity, since houses are expected to sell for less when the buyer is experiencing extremely hot weather during the time of transaction. This implies that valuing climate amenities are important to individuals when purchasing a house.

We test for robustness of estimates in our sample by including several model specifications in addition to yearly, monthly and neighborhood fixed effects to capture any unobserved amenities to address the concern of omitted variable bias. With the addition of the interaction term, we find weak evidence homes with higher market improvement value (top 25%) that are assumed to more likely to have AC or energy efficiency capabilities, therefore the UHI effect has a statistically insignificant total effect on them. Another reason that this evidence may be weak is that homeowners are unaware of the value of energy efficiency therefore, this is not reflected in the price of a house. One possible extension of this study would be to increase the number of observations in our sample and look at the recent 10 years (2010-present) for both housing and climate data. Along with this, looking at housing transactions that are beyond this university town would provide insight on how hotter temperatures effect housing prices in other metro areas. This can potentially be measured by creating spatial buffers for parcels that are in close proximity to the boundary, similar to previous studies that captures the effect of environmental amenities and dis-amenities through proximity measures (Daams et. al 2016; Affuso et. al 2019). Given that the CoreLogic data for A/C in homes for the sample was unavailable, another extension of this study would be to use energy score reports as a proxy, because these reports estimate the energy use, cost of utilities, and cost-effective energy solutions for homes. For equity and housing affordability purposes, reducing this energy burden is important to keep this in mind since there is evidence that the most vulnerable populations, like low-income communities are heavily impacted by the UHI effect. Lastly, since the Eugene-Springfield metro area is in a smaller spatial scale compared to a larger city, studying the influence of the UHI effect on housing prices in Portland, OR may also provide insight on how the UHI effect can vary at a larger spatial scale.

Policy Implications

The negative impact of the UHI on housing prices has potential implications at the city and county level because we can expect that officials will be able to collect less property taxes, especially for metro areas that experience an intense UHI effect. The evidence from this study also provides implications for policy measures to mitigate the UHI effect. Taking the impact of the UHI effect on housing prices into account can influence the behavior of home buyers/sellers and real estate agents because they can advertise according to the upgrades made to the energy or cooling efficiency of a structure. This may incentivize homeowners to make improvements to the energy efficiency of homes, however this maybe challenging if a homeowner does not have the financial capability of doing so or if the structure is really old, further creating barriers to entry in the market for energy efficiency of homes with lower market improvement values.

Another incentive of reporting energy scores of homes is that it raises the value of homes resulting in a higher transaction price transaction for a parcel (Myers et. al 2019). Policymakers can require home energy scores to be evaluated then reported in home sale documents so that efficiency can be explicitly priced into decisions with complete information of the energy burden associated with the home and incentivize investments in the energy efficiency of homes. They can do this by subsidizing efficiency and cooling upgrades for low income communities' homeowners, which further reduces the barriers to entry in the market and ensures affordable housing for various demographic groups in urban areas. Other policy interventions include making adjustments to infrastructure like green roofs, improving electric grid resiliency, permeable pavements, bioswales, and implementing urban forests to mitigate the retainment of extreme heat in the environment. Reframing the UHI effect in the housing market provides further insight on how policymakers can address climate change issues given the economic disparity and health risks it causes in metropolitan areas.

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Appendix A Full Tables of Results for all Models

1. Results of Log-Linear Model with all Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	loglag	log1	log2	log3	log4	log5	log6	log7
avg_temp dev	-0.00681		-0.00592					
	(0.00562)		(0.00559)					
avg_temp dev_lag	-0.00804	-0.00846	-0.00989*	-0.0103*				
	(0.00584)	(0.00583)	(0.00585)	(0.00584)				
avg_temp dev # top25	0.0179**		0.0163*					
	(0.00909)		(0.00915)					
avg_temp dev_lag # top25	-0.00369	-0.00228	-0.00497	-0.00372				
	(0.00349)	(0.00326)	(0.00353)	(0.00330)				
acres	0.00434	0.00705	0.0104	0.0123	0.00313	0.00637	0.00860	0.0108
	(0.0485)	(0.0492)	(0.0500)	(0.0507)	(0.0493)	(0.0497)	(0.0508)	(0.0511)
year1	0.233***	0.238***	0.228***	0.232***	0.245***	0.241***	0.240***	0.237***
	(0.0198)	(0.0196)	(0.0198)	(0.0193)	(0.0184)	(0.0181)	(0.0185)	(0.0182)
year2	-0.0396**	-0.0355**	-0.0457**	-0.0423**	-0.0360*	-0.0393**	-0.0422**	-0.0451**
	(0.0193)	(0.0180)	(0.0196)	(0.0181)	(0.0199)	(0.0184)	(0.0199)	(0.0185)

year3	-0.342***	-0.337***	-0.346***	-0.343***	-0.332***	-0.346***	-0.337***	-0.349***
	(0.0307)	(0.0243)	(0.0308)	(0.0248)	(0.0309)	(0.0245)	(0.0306)	(0.0251)
lnImpValue	0.722***	0.732***	0.702***	0.711***	0.722***	0.736***	0.701***	0.714***
	(0.0237)	(0.0224)	(0.0237)	(0.0225)	(0.0226)	(0.0221)	(0.0227)	(0.0223)
Month of Sale=5	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Month of Sale=6	-0.0406	-0.0436	-0.0604	-0.0631	-0.0887	-0.0920	-0.104	-0.107
	(0.0605)	(0.0606)	(0.0604)	(0.0605)	(0.0712)	(0.0710)	(0.0721)	(0.0721)
Month of Sale=7	-0.0737	-0.0776	-0.0882	-0.0915	-0.147*	-0.141*	-0.158**	-0.152*
	(0.0629)	(0.0624)	(0.0627)	(0.0621)	(0.0789)	(0.0785)	(0.0803)	(0.0797)
Month of Sale=8	-0.0105	-0.0114	-0.0263	-0.0271	-0.0648	-0.0626	-0.0776	-0.0752
	(0.0586)	(0.0584)	(0.0586)	(0.0583)	(0.0700)	(0.0701)	(0.0725)	(0.0726)
Month of Sale=9	-0.0458	-0.0484	-0.0648	-0.0671	-0.105	-0.101	-0.120*	-0.115
	(0.0571)	(0.0569)	(0.0567)	(0.0565)	(0.0700)	(0.0699)	(0.0714)	(0.0712)
prism grid=13	0	0			0	0		
	(.)	(.)			(.)	(.)		

prism grid=14	-0.0779**	-0.0769**			-0.0766**	-0.0769**		
	(0.0335)	(0.0333)			(0.0337)	(0.0336)		
prism grid=15	-0.0691*	-0.0706*			-0.0719*	-0.0712*		
	(0.0409)	(0.0409)			(0.0414)	(0.0413)		
prism grid=16	-0.0819**	-0.0831**			-0.0836**	-0.0831**		
	(0.0401)	(0.0403)			(0.0406)	(0.0405)		
prism grid=20	-0.0701**	-0.0714**			-0.0731**	-0.0743**		
	(0.0303)	(0.0305)			(0.0306)	(0.0307)		
prism grid=21	-0.131***	-0.130***			-0.130***	-0.130***		
	(0.0325)	(0.0326)			(0.0329)	(0.0329)		
prism grid=22	-0.0268	-0.0238			-0.0275	-0.0243		
	(0.0366)	(0.0368)			(0.0374)	(0.0373)		
prism grid=23	-0.150***	-0.150***			-0.154***	-0.152***		
	(0.0395)	(0.0398)			(0.0404)	(0.0404)		
prism grid=24	-0.0967**	-0.0951**			-0.100**	-0.0968**		
	(0.0462)	(0.0463)			(0.0467)	(0.0467)		

prism grid=25	-0.0385	-0.0423			-0.0429	-0.0450		
	(0.0614)	(0.0619)			(0.0622)	(0.0623)		
prism grid=31	-0.170***	-0.166***			-0.171***	-0.167***		
	(0.0339)	(0.0337)			(0.0344)	(0.0342)		
prism grid=32	0.0748	0.0759			0.0728	0.0753		
	(0.0852)	(0.0849)			(0.0854)	(0.0852)		
prism grid=33	-0.0424	-0.0446			-0.0425	-0.0436		
	(0.114)	(0.113)			(0.114)	(0.113)		
prism grid=34	-0.0897**	-0.0911**			-0.0934**	-0.0932**		
	(0.0378)	(0.0382)			(0.0384)	(0.0386)		
prism grid=35	-0.0845**	-0.0859**			-0.0871**	-0.0878**		
	(0.0348)	(0.0348)			(0.0355)	(0.0355)		
prism grid=36	-0.295***	-0.292***			-0.298***	-0.293***		
	(0.0679)	(0.0680)			(0.0688)	(0.0685)		
prism grid=37	-0.118***	-0.119***			-0.126***	-0.123***		
	(0.0360)	(0.0363)			(0.0376)	(0.0375)		

prism grid=38	-0.132***	-0.134***			-0.138***	-0.140***		
	(0.0351)	(0.0353)			(0.0366)	(0.0365)		
prism grid=44	-0.0333	-0.0335			-0.0388	-0.0406		
	(0.0340)	(0.0340)			(0.0352)	(0.0352)		
prism grid=45	-0.0286	-0.0321			-0.0326	-0.0386		
	(0.0435)	(0.0434)			(0.0445)	(0.0445)		
Census Tract=10			0	0			0	0
			(.)	(.)			(.)	(.)
Census Tract=18			-0.289***	-0.307***			-0.302***	-0.322***
			(0.0608)	(0.0611)			(0.0600)	(0.0608)
Census Tract=19			-0.343***	-0.358***			-0.354***	-0.370***
			(0.0646)	(0.0653)			(0.0643)	(0.0652)
Census Tract=20			-0.232***	-0.248***			-0.241***	-0.259***
			(0.0642)	(0.0649)			(0.0636)	(0.0648)
Census Tract=21			-0.342***	-0.360***			-0.352***	-0.370***
			(0.0841)	(0.0833)			(0.0837)	(0.0831)

Census Tract=22			-0.216***	-0.234***			-0.223***	-0.241***
			(0.0607)	(0.0611)			(0.0594)	(0.0608)
Census Tract=23			-0.249***	-0.264***			-0.254***	-0.272***
			(0.0591)	(0.0592)			(0.0579)	(0.0593)
Census Tract=24			-0.156***	-0.173***			-0.161***	-0.180***
			(0.0596)	(0.0593)			(0.0597)	(0.0601)
Census Tract=25			-0.244***	-0.261***			-0.251***	-0.271***
			(0.0589)	(0.0589)			(0.0577)	(0.0588)
Census Tract=26			-0.313***	-0.329***			-0.318***	-0.336***
			(0.0610)	(0.0612)			(0.0603)	(0.0615)
Census Tract=27			-0.414***	-0.429***			-0.417***	-0.437***
			(0.0878)	(0.0873)			(0.0869)	(0.0875)
Census Tract=28			-0.236***	-0.253***			-0.240***	-0.259***
			(0.0648)	(0.0648)			(0.0638)	(0.0649)
Census Tract=29			-0.240***	-0.257***			-0.245***	-0.263***

			(0.0631)	(0.0629)			(0.0612)	(0.0625)
Census Tract=30			-0.140**	-0.153**			-0.146**	-0.160***
			(0.0615)	(0.0617)			(0.0607)	(0.0616)
Census Tract=31			-0.201***	-0.217***			-0.211***	-0.227***
			(0.0603)	(0.0608)			(0.0596)	(0.0609)
Census Tract=32			-0.447***	-0.465***			-0.456***	-0.475***
			(0.0775)	(0.0783)			(0.0766)	(0.0780)
Census Tract=33			-0.248***	-0.263***			-0.258***	-0.274***
			(0.0862)	(0.0865)			(0.0858)	(0.0861)
Census Tract=34			-0.507***	-0.517***			-0.517***	-0.527***
			(0.142)	(0.143)			(0.142)	(0.143)
Census Tract=35			-0.245***	-0.263***			-0.253***	-0.273***
			(0.0610)	(0.0609)			(0.0600)	(0.0609)
Census Tract=36			-0.228***	-0.243***			-0.235***	-0.252***
			(0.0787)	(0.0794)			(0.0773)	(0.0791)

Census Tract=37			-0.0516	-0.0782			-0.0659	-0.0902
			(0.0704)	(0.0678)			(0.0679)	(0.0673)
Census Tract=39			-0.372	-0.388			-0.373	-0.395
			(0.350)	(0.350)			(0.348)	(0.350)
Census Tract=40			-0.111	-0.124			-0.117	-0.131
			(0.114)	(0.114)			(0.114)	(0.115)
Census Tract=41			-0.307***	-0.325***			-0.314***	-0.335***
			(0.0944)	(0.0941)			(0.0927)	(0.0939)
Census Tract=42			-0.414***	-0.427***			-0.416***	-0.430***
			(0.135)	(0.135)			(0.133)	(0.134)
Census Tract=43			-0.362***	-0.373***			-0.368***	-0.381***
			(0.0661)	(0.0663)			(0.0657)	(0.0664)
Census Tract=44			-0.177***	-0.193***			-0.186***	-0.205***
			(0.0560)	(0.0579)			(0.0564)	(0.0581)
Census Tract=45			-0.213**	-0.223**			-0.228**	-0.225**
			(0.101)	(0.107)			(0.0939)	(0.103)

Census Tract=46			-0.274	-0.292			-0.277	-0.300
			(0.204)	(0.203)			(0.204)	(0.204)
Census Tract=47			-0.0855	-0.108			-0.0939	-0.123
			(0.0875)	(0.0878)			(0.0864)	(0.0887)
Census Tract=48			-0.0990	-0.105			-0.0932	-0.112*
			(0.0698)	(0.0654)			(0.0666)	(0.0656)
Census Tract=49			-0.191	-0.209			-0.190	-0.213
			(0.206)	(0.205)			(0.207)	(0.205)
Census Tract=50			-0.183***	-0.203***			-0.192***	-0.216***
			(0.0619)	(0.0617)			(0.0608)	(0.0614)
Census Tract=51			-0.196*	-0.214**			-0.212*	-0.236**
			(0.112)	(0.109)			(0.112)	(0.108)
Census Tract=52			-0.244**	-0.260**			-0.253**	-0.274**
			(0.107)	(0.106)			(0.106)	(0.107)
Census Tract=53			-0.143*	-0.157*			-0.155*	-0.171**
			(0.0842)	(0.0831)			(0.0827)	(0.0831)

Census Tract=54			-0.184***	-0.199***			-0.196***	-0.214***
			(0.0589)	(0.0586)			(0.0578)	(0.0584)
max_tempdev					-0.000889		-0.000962	
					(0.00500)		(0.00494)	
max_tempdev_lag					-0.00897*	-0.00917*	-0.00996**	-0.0101**
					(0.00493)	(0.00493)	(0.00504)	(0.00503)
max_tempdev # top25					0.0161**		0.0151**	
					(0.00655)		(0.00662)	
max_tempdev_lag # top25					-0.00411*	-0.00255	-0.00502**	-0.00359
					(0.00249)	(0.00232)	(0.00251)	(0.00235)
Constant	3.741***	3.609***	4.165***	4.061***	3.794***	3.628***	4.226***	4.092***
	(0.297)	(0.284)	(0.290)	(0.279)	(0.296)	(0.290)	(0.292)	(0.288)
Observations	3532	3532	3532	3532	3532	3532	3532	3532
R^2	0.495	0.495	0.498	0.498	0.496	0.495	0.499	0.498
Adjusted R^2	0.491	0.490	0.491	0.491	0.491	0.491	0.492	0.491

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2. Results of Linear Model with all Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lag	lag1	lag2	lag3	lag4	lag5	lag6	lag7
avg_tempdev	-28875.1**		-28096.2**					
	(12994.6)		(13080.7)					
avg_tempdev_lag	5477.5	5468.1	4167.3	3410.7				
	(6233.8)	(6469.3)	(5720.2)	(5471.8)				
avg_tempdev # top25	-19429.9	-32241.5	-16840.9					
	(21476.2)	(21834.9)	(21513.1)					
avg_tempdev_lag # top25	3595.7		3122.8	1282.4				
	(3799.3)		(3858.1)	(2355.7)				
acres	-129362.3**	-136212.5**	-170000.9**	-177159.1**	-134134.7**	-137982.0**	-173089.2**	-176144.2**
	(62616.9)	(66062.3)	(82802.9)	(86371.0)	(63934.4)	(66178.7)	(83441.0)	(85285.9)
year1	102139.1***	148562.3***	94015.2***	152149.6***	132654.1***	159788.1***	134848.6***	158718.4***
	(20591.1)	(38085.4)	(17350.9)	(41962.1)	(28613.5)	(40982.9)	(30480.9)	(42109.9)
year2	-29048.3**	5792.6	-36578.4**	6278.7	-14624.9	16133.0	-10161.7	17233.4
	(13905.8)	(12837.6)	(14246.9)	(12473.1)	(11293.5)	(15742.5)	(9264.3)	(15906.6)

year3	-158250.9***	-85432.1***	-154659.8***	-58298.9***	-121749.9***	-56282.4***	-92127.9***	-35594.8
	(36082.6)	(19532.2)	(33441.0)	(17279.6)	(25563.9)	(17984.3)	(13227.4)	(24624.7)
Improvement Value	1.261***	1.358***	1.080***	1.053***	1.194***	1.215***	1.005***	1.046***
	(0.185)	(0.223)	(0.175)	(0.126)	(0.143)	(0.129)	(0.135)	(0.121)
Month of Sale=5	0	0	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Month of Sale=6	69689.0	55969.3	52263.3	38957.5	44322.6	69020.9	110125.1	132049.0
	(65385.3)	(60889.0)	(58787.5)	(54124.8)	(59427.4)	(68794.2)	(84716.1)	(94909.7)
Month of Sale=7	104694.0	63628.5	91344.5	40695.1	90863.2	71783.8	164206.2	148139.0
	(83173.9)	(68619.1)	(78881.6)	(58508.2)	(87168.2)	(78874.8)	(118773.4)	(110491.2)
Month of Sale=8	204051.2*	193782.4*	194732.7*	182082.4*	203342.6*	206216.1*	269197.5*	272476.0*
	(115134.6)	(111144.6)	(114450.4)	(108986.7)	(120506.1)	(121167.5)	(152458.9)	(153311.5)
Month of Sale=9	102149.7	78104.1	97205.6	67735.6	98923.9	85784.6	174847.4*	164094.4
	(68547.2)	(60401.5)	(66679.3)	(54623.7)	(73176.0)	(67417.3)	(105506.5)	(99755.9)
prism grid=13	0	0			0	0		
	(.)	(.)			(.)	(.)		

prism grid=14	-87859.9***	-81352.9***			-83831.8***	-80305.9***		
	(22584.0)	(21229.8)			(21919.4)	(21226.1)		
prism grid=15	-75002.2***	-77618.0***			-74008.8***	-74675.5***		
	(24196.0)	(24083.7)			(23329.6)	(23250.2)		
prism grid=16	-85074.6***	-89126.2***			-86672.5***	-88609.1***		
	(24270.1)	(24196.5)			(24003.2)	(24090.2)		
prism grid=20	-72319.8***	-78122.7***			-71511.0***	-75810.5***		
	(19744.1)	(20200.5)			(20187.0)	(20335.0)		
prism grid=21	-91678.3***	-92224.7***			-90429.6***	-92850.7***		
	(20729.5)	(20600.0)			(20716.2)	(20830.0)		
prism grid=22	-61123.7***	-63627.2***			-68207.7***	-71837.3***		
	(20962.5)	(20986.0)			(22167.0)	(22674.3)		
prism grid=23	-79492.2***	-87685.1***			-85459.0***	-91737.5***		
	(19235.5)	(19737.5)			(20193.8)	(20710.1)		
prism grid=24	-56602.7***	-58695.5***			-65379.8***	-65067.1***		

	(21783.9)	(21935.2)			(22031.7)	(21721.6)		
prism grid=25	-54673.6**	-68743.2***			-61172.4**	-69033.7***		
	(26060.1)	(25412.3)			(25986.2)	(25567.6)		
prism grid=31	-64567.4***	-59534.4**			-66718.2***	-64576.9***		
	(22396.7)	(23254.3)			(22130.3)	(21972.0)		
prism grid=32	690403.4**	690302.0**			687742.0**	689381.0**		
	(332366.9)	(333025.2)			(332650.0)	(333408.5)		
prism grid=33	-77680.7	-75028.9			-74334.5	-73401.9		
	(51907.6)	(49941.1)			(49635.1)	(48808.5)		
prism grid=34	-78922.5***	-88558.4***			-84831.7***	-88821.2***		
	(21327.7)	(21743.1)			(21675.5)	(21983.0)		
prism grid=35	-80133.2***	-86610.2***			-85712.7***	-85727.9***		
	(20448.5)	(21232.7)			(21470.4)	(21294.7)		
prism grid=36	-83877.9***	-86109.7***			-95062.1***	-92102.7***		
	(24848.5)	(25325.4)			(24477.2)	(24307.9)		

prism grid=37	-48104.3**	-58600.6***			-60442.6***	-58988.1***		
	(21153.7)	(20963.4)			(21649.9)	(21690.2)		
prism grid=38	-71808.9***	-81657.4***			-81870.7***	-77351.0***		
	(19777.7)	(19756.5)			(20834.3)	(20884.4)		
prism grid=44	-72376.9***	-72943.3***			-75281.0***	-68618.0***		
	(22964.5)	(22844.0)			(23631.3)	(23062.7)		
prism grid=45	-73064.1**	-72514.6***			-69573.7**	-62363.5**		
	(28894.6)	(27416.9)			(27780.7)	(26899.5)		
Census Tract=10			0	0			0	0
			(.)	(.)			(.)	(.)
Census Tract=18			-257171.0**	-229206.1*			-218767.4*	-219693.2*
			(128392.6)	(122162.8)			(120927.2)	(119619.6)
Census Tract=19			-264726.5**	-237109.5*			-230258.1*	-229808.8*
			(128525.0)	(123738.5)			(123086.5)	(121940.6)
Census Tract=20			-244425.3*	-217693.1*			-207183.8*	-212533.1*

			(127982.3)	(122213.6)			(120931.8)	(120838.3)
Census Tract=21			-284780.0**	-257303.2**			-244075.5**	-252244.2**
			(131967.6)	(125754.4)			(124081.3)	(124616.6)
Census Tract=22			-259746.0*	-223374.1*			-214025.4*	-218728.6*
			(134177.7)	(123667.4)			(123339.8)	(122611.6)
Census Tract=23			-257314.6**	-220318.8*			-213078.8*	-215229.6*
			(130476.7)	(122200.5)			(122221.4)	(121409.4)
Census Tract=24			-202067.3	-160728.3			-152233.9	-155376.3
			(133540.4)	(123523.5)			(123864.1)	(122919.2)
Census Tract=25			-273284.1**	-237859.7*			-223602.3*	-229708.0*
			(133201.2)	(125033.3)			(123540.9)	(123436.0)
Census Tract=26			-278817.9**	-241303.9*			-232262.8*	-236809.0*
			(130911.7)	(123123.8)			(122931.3)	(122627.9)
Census Tract=27			-306234.6**	-261515.4**			-252133.0**	-255643.1**
			(137315.6)	(126549.0)			(126749.1)	(125800.7)

Census Tract=28			-261561.9*	-227645.8*			-214269.4*	-223728.8*
			(133725.4)	(125574.6)			(124490.3)	(125020.1)
Census Tract=29			-279803.1**	-244213.6*			-233976.9*	-240033.1*
			(137516.7)	(126481.9)			(126108.7)	(125514.3)
Census Tract=30			-234044.5*	-208489.9*			-199524.9	-204757.4*
			(130506.5)	(124890.7)			(123950.4)	(123976.0)
Census Tract=31			-260031.1**	-234708.4*			-221816.9*	-229498.2*
			(131865.3)	(125827.6)			(123913.9)	(124419.8)
Census Tract=32			-281178.9**	-253232.9**			-238644.3*	-247474.5**
			(130762.1)	(124199.3)			(122386.1)	(122964.5)
Census Tract=33			-257769.0**	-231348.3*			-219866.1*	-224308.1*
			(126918.8)	(122783.2)			(121549.6)	(121301.6)
Census Tract=34			-297839.1**	-265266.7**			-263155.5**	-259909.5**
			(134749.2)	(129198.1)			(128837.8)	(127873.3)
Census Tract=35			-273327.3**	-241224.0*			-232994.8*	-236280.0*

			(134449.5)	(126455.8)			(126283.1)	(125293.5)
Census Tract=36			-252663.9**	-226300.8*			-214675.1*	-220936.8*
			(128408.5)	(121604.2)			(120369.7)	(120188.8)
Census Tract=37			-305565.2*	-244709.9*			-239295.5	-239008.4
			(177629.7)	(148061.9)			(150840.8)	(146132.4)
Census Tract=39			-272981.2*	-249863.8*			-230203.8	-241824.4*
			(153495.4)	(146595.4)			(145033.9)	(144811.7)
Census Tract=40			-196322.2	-164843.8			-154526.9	-162623.1
			(124538.4)	(119798.5)			(118328.5)	(119060.7)
Census Tract=41			-272188.9**	-238453.9*			-222442.2*	-232300.2*
			(132885.0)	(124749.8)			(123116.0)	(123556.1)
Census Tract=42			-315282.7**	-280686.9**			-272415.1**	-281173.3**
			(144780.3)	(134883.8)			(136471.9)	(135406.4)
Census Tract=43			-266031.4**	-227448.2*			-226211.4*	-222495.0*
			(128653.8)	(122016.9)			(123005.1)	(121365.6)

Census Tract=44			2735.3	42454.7			51416.7	51250.8
			(109689.5)	(120817.7)			(118337.4)	(122084.6)
Census Tract=45			-245226.0*	-234438.0*			-225246.9*	-236718.6*
			(134061.8)	(129567.8)			(127373.4)	(130366.1)
Census Tract=46			-254978.8*	-209875.4*			-204089.0	-202868.7
			(137332.8)	(126929.9)			(128424.5)	(126002.1)
Census Tract=47			-233998.3*	-187362.3			-184338.8	-177899.8
			(132000.5)	(119843.9)			(120423.8)	(118078.0)
Census Tract=48			-442896.0**	-364299.2**			-380878.2**	-362927.9**
			(203055.0)	(174508.7)			(184740.3)	(174553.8)
Census Tract=49			-195457.0	-149230.1			-145587.5	-146875.7
			(158612.4)	(145803.5)			(147750.2)	(145417.8)
Census Tract=50			-248198.6*	-203363.8*			-192490.6	-191347.8
			(133794.5)	(121402.7)			(121076.2)	(118588.0)
Census Tract=51			-247059.8*	-198714.3			-178632.3	-177379.8

			(133483.3)	(125161.1)			(119524.1)	(119222.4)
Census Tract=52			-241439.1*	-211136.9*			-202059.6*	-199019.1*
			(129980.7)	(122975.4)			(122027.5)	(119845.8)
Census Tract=53			-236170.4*	-205454.3*			-194913.2	-196664.1
			(130906.7)	(124347.4)			(122678.2)	(121859.3)
Census Tract=54			-232854.6*	-197808.5			-190491.9	-186930.7
			(128138.5)	(120533.0)			(119573.8)	(117733.9)
max_tempdev					-18858.6**		-17666.0**	
					(8570.8)		(8171.6)	
max_tempdev_lag					4191.4	4087.9	9012.0	8863.0
					(4780.1)	(4785.5)	(6748.3)	(6729.0)
max_tempdev # top25					3060.0		7422.7	
					(5323.1)		(4527.7)	
max_tempdev_lag # top25					1546.9	1678.8	980.8	1527.2
					(2218.8)	(1845.8)	(2179.7)	(1937.7)

Constant	20980.0	-40424.5	269152.7**	182092.0	18528.5	-43856.1	117349.6	60697.1
	(93500.6)	(114613.6)	(112724.1)	(115166.1)	(97016.7)	(117546.6)	(120786.9)	(134491.6)
Observations	3532	3532	3532	3532	3532	3532	3532	3532
R^2	0.076	0.074	0.051	0.049	0.074	0.073	0.050	0.049
Adjusted R^2	0.067	0.066	0.038	0.036	0.065	0.065	0.036	0.036

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$