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SOME LIKE IT (LESS) HOT:
EXTRACTING TRADEOFF MEASURES FOR PHYSICALLY COUPLED AMENITIES

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ABSTRACT

The Urban Heat Island (UHI) provides direct evidence of how human activities contribute to a feedback loop that can result in multiple changes in ecosystem services by creating localized warming as well as differences in vegetated landscapes in areas surrounding the urban core. This paper develops a new spatial-temporal panel estimator to recover consistent estimates of household valuation of coupled landscape and temperature ecosystem services. Using data from Phoenix, AZ, we estimate a hedonic price function using an extension of the Hausman-Taylor model. The framework adapts the earlier Abbott Klaiber [2011] proposal to overcome challenges associated with the varying spatial scales of capitalization of landscape and temperature variables and the likelihood of spatially and temporally varying omitted variables. We find a positive and economically significant marginal willingness to pay (MWTP) for measures of green landscaping at multiple spatial scales and a separate, MWTP for a one degree (F) reduction in outdoor temperatures of $56 monthly.

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I. Introduction

Hedonic models have been used to estimate measures for the economic tradeoffs people would make, at the margin, to enhance (or avoid degradation in) a wide array of outdoor amenities. Some examples directly related to land use decisions include forest lands (Cho, Poudyal and Roberts 2008; Thorsnes 2002; Tyrvainen and Miettinen 2000), greenbelts (Lee and Linneman 1998), wetlands (Mahan, Polasky and Adams 2000), lakes (Abbott and Klaiber 2013), open space (Abbott and Klaiber 2010; Geoghegan 2002; Irwin and Bockstael 2001; Smith, Poulos and Kim 2002; Towe 2009), and aspects of the surrounding landscape, including tree canopy cover (Cavailhes 2009; Geoghegan, Wainger and Bockstael 1997; Luttik 2000; Netusil, Chattopadhyay and Kovacs 2010; Sander, Polasky and Haight 2010). In contrast to these applications, the use of hedonic property value models for the case of landscape related amenities presents dual challenges.

First, landscape amenities may convey multiple benefits of varying levels of excludability, leading to complex, multi-scalar patterns of capitalization. For example, tree cover on one's property may convey excludable benefits due to its role in shading the house, providing privacy or enhancing the recreational utility of the yard. Trees on the edge of a neighbor's yard may provide valuable privacy benefits, while the trees of still more distant neighbors may offer more diffused aesthetic benefits or improvements to the neighborhood micro-climate. Tree cover, and landscaping more generally, contributes to creating a multidimensional impure public good with implications that can have confounding effects on what can be learned from models that rely on spatial differences in housing prices.

Second, landscape amenities, by the nature of their interactions with the built and natural environment may also serve as factor inputs to other valued amenities. For example, vegetation through the effects of shade and evapotranspiration may act to moderate local temperatures. The urban heat island (UHI) – the relative warming of built urban areas compared to surrounding non-urban areas – is an intensively researched micro-climatic effect of people's decisions to transform the landscape. Extensive research in Phoenix, much of it funded under the National Science Foundation's CAP-LTER program, has demonstrated an urban heat island (UHI) effect from the urbanization of its landscape.[1] For economists, efforts to understand how these changes feedback into household decision making, and what these decisions, in turn, reveal about the value placed on these amenities are critical inputs for the design of policies to mitigate heat island effects.

The hypothesis that people recognize the UHI and adapt their activities to mitigate its effects within a given urban area has *not* been tested in the existing literature. We provide the first unambiguous evidence of an important feedback loop between UHI, people's behavior through the location of their housing choice, and the resulting changes in landscape. We establish this finding by jointly estimating the effects of temperature and the presence of water-intensive ("green") landscaping on housing prices for single-family residential properties in the Phoenix metropolitan area.[2] This task is accomplished while taking account of other location specific amenities and dis-amenities, including the role of site elevation[3].

Green landscaping provides both private and public benefits to residents at multiple spatial scales. It serves to mitigate the UHI effects on local temperatures. Private benefits also include the aesthetic value of a green yard as well as the opportunity for local outdoor recreation allowed by the

[1] See Grimm and Redman [2004] for a summary of the multiple dimensions of this transformation.
[2] Baker et al. [2002] suggest mechanisms that could lead to feedbacks but do not provide evidence that the temperature effects and recognized choices lead to real resource commitments that can be associated with the temperatures that vary with location and time of the housing sales.
[3] A home's elevation potentially influences both vistas and evening temperatures linked to the site.

grass. At a neighborhood scale, the quantity of green landscape may provide services through aesthetics and recreational opportunities in public areas.

Landscape changes take place within a finely delineated spatial template. This setting combines structures, roads, and other features of the built environment with the natural environment. The landscaping decisions of homeowners in a given neighborhood collectively influence localized daily maximum and nighttime minimum temperatures. By transforming landscape on their properties homeowners produce local amenities for themselves and, indirectly, spillovers for their neighbors. Homeowners' associations also produce collective amenities in their respective local neighborhoods through plantings, water features, maintenance programs for open space, and restrictions on what homeowners can do – all of which can affect the microclimate (see Chow et al. [2012]). People's behavior, together with the natural processes, are thus jointly embedded in the hedonic price equilibrium which is assumed to give rise to the relationship between housing prices, home attributes, and spatially varying features of parcels and neighborhoods (as well as other local goods such as local school quality, safety and other dimensions of environmental quality).

The implication of this logic for the measurement of the tradeoffs households would make to enhance landscape amenities arises because the multiple induced outputs resulting from their choices must be considered as joint outcomes. A strategy that does not adequately control for the roles that landscape inputs play in the hedonic price function will provide inconsistent estimates of the marginal value of temperature. It could easily confound the separate effects of the services provided by landscape amenities with landscape effects on temperature mitigation. Even if concern lies only with estimating the overall marginal value of landscape, inclusive of its induced effects on temperature, there is still a need to account for both landscape and temperature due to the potential for reverse causation. To address this challenge we modify Abbott and Klaiber's [2011] extension to the Hausman-Taylor panel data model for a hierarchical spatial context. Our strategy extends their logic by defining panels that exploit two sources of variation in housing prices—the spatial and the temporal dimensions.

The next section describes the urban heat island and its link to landscaping choices. It then discusses important differences between our approach and past efforts to measure the effect of weather variables on housing prices, wages, or migration choices. Section 3 presents our econometric model. Sections 4 and 5 describe the data used and estimation results, respectively. Section 6 discusses the complementarities between the use of hedonic methods to estimate the effects of spatially delineated amenities and the modeling of urban ecosystems.

II. The Urban Heat Island and Landscape

The urban heat island refers to the records documenting warmer temperatures at the core of a built urban area compared to its surrounding, more rural, areas that fall within the same general weather patterns. It is one of the best documented weather related phenomena that can be associated with the increases in urbanization globally (see Oke [1982]). Grimm and Redman's [2004] summary of the first five years of research associated with the CAP-LTER notes that:

> "The signal (for the UHI) in Phoenix is much more dramatic than other world city sites at 10 times the global change trend, owing to the stable air and clear days in this desert city. Minimum temperatures in the Phoenix summertime have increased by 10°C over the last 50 years . . ." (P. 208, parenthetical phrase added).

The UHI effect is typically greater at night when energy stored in impervious surfaces is released to the atmosphere, dampening the typical pattern of nighttime cooling – so much so that the UHI is often defined on the basis of nighttime temperatures.

There are multiple sets of research that have confirmed the general trends Grimm and Redman highlight. For example, Brazel et al. [2007] examined the areas around surface weather stations between 1990 and 2004. Using a pooled sample (over years and spatial zones) this study found that monthly mean minimum temperatures for June in each of thirty-seven development zones were significantly related to new housing units built in each zone after controlling for the land types used to define their zones. Mean minimum temperatures increased by approximately 1.4°C (2.5°F) for each 1000 new homes constructed around the station in each year. While the authors are careful to qualify their results as an approximate relationship that is supportive of UHI effects, they nonetheless reinforce the conclusions based on other results tracking the general trends in temperature and urbanization for the area as a whole.

The economic literature on the effects of temperature on housing prices is relatively small. For the most part models considering temperature as influencing house prices or wages assume households sort across multiple metropolitan areas and employment markets in response to spatially aggregated measures of regional climate.[4] This literature generally involves multiple metropolitan areas and jointly considers changes in housing prices (rents) along with wages. The conceptual arguments for joint consideration of wages and rents are usually attributed to Rosen [1979] and Roback [1982]. The first empirical effort to evaluate the model's implications was developed by Blomquist et al. [1988]. Their findings clearly supported weather conditions as a factor in a model that assumed rents and wages were determined cross metro areas as a result of a long-run sorting process. Most recently, two studies have extended their analyses in somewhat different directions. Bieri, Kuminoff, and Pope [2014] consider the effects of 75 amenities for over 3000 counties in the U.S. on wages and annualized housing prices. Their analysis includes geographic features, environmental amenities (and dis-amenities), local public services, infrastructure, and cultural and urban amenities. Humidity, heating and cooling degree days, precipitation, and sunshine are their weather related variables. In their preferred model with all 75

[4] See Albouy et al. [2013]; Biere et al.[2014]; Cragg and Kahn [1997]; Maddison and Bigano [2003]; Rehdanz and Maddison [2009]; Sinha and Cropper [2013].

amenities, cooling degree days are a significant *negative* influence on rents and their measure for sunshine is a significant positive influence.[5]

Plantinga et al. [2013] supplements the Blomquist et al. logic using a random utility model (RUM) of location choices across metropolitan areas. The primary source for their data is the 2000 5% Public Use Microdata Survey. They consider migration decisions between 1995 and 2000 for working age (aged 25 to 64) adults for 291 metropolitan areas (MA). In a migration model they find that higher January temperatures attract movers and higher July temperatures are a significant deterrent.[6]

Our analysis is different from these other efforts in that it requires that an economically important choice, the housing decision, respond over relatively small variations in local weather conditions within a single metropolitan area. It does have some advantages in that it can take advantage of spatially stable gradients of temperature within the housing market provided they are known to a significant share of homebuyers. There are several reasons to suggest this characterization is reasonable. First, there is significant heterogeneity in heat exposure across Maricopa County. 63% of the spatial-temporal variability in mean minimum temperatures at the Census tract level can be explained by spatial heterogeneity in the means alone. Second, previous work has demonstrated a strong correlation of income and lower summer surface temperatures that is suggestive of sorting behavior in the market, with a marginal reduction of 0.28°C for every $10,000 in income (Jenerette et al. [2007]). This same work has shown that much of the income-based heterogeneity of temperatures is driven by differences of vegetative cover, buttressing the case for the joint consideration of these amenities.[7]

[5] A small number of other studies have also considered weather's role. See Albouy et al. [2013]; Cragg and Kahn [1997]; Maddison and Bigano [2003]; Rehdanz and Maddison [2009]; Sinha and Cropper [2013].

[6] A simpler migration analysis by Evans et al. [2014] using the 2004 and 2006 waves together with confidential records identifying the census tract of respondents to evaluate residential choices in 2006 confirms the importance of weather variables.

[7] In unpublished research using stated preference questions, Smith et al. [2007] asked respondents from the Phoenix, AZ area whether they would be willing to pay a higher mortgage or rental fee to reduce summer nighttime temperatures. The analysis found that respondents were willing on average to pay nearly $40 a month for a reduction of 5 degrees Fahrenheit.

Finally, a separate set of research has used the American time use survey to consider how people adapt to short term variations in weather conditions. Graff-Zivin and Neidell document a robust link between temperature and individuals' daily time allocations to working outdoors for surveys between 2003 and 2006. Their analysis focuses on industries classified as likely to involve work outside. There are monotonic declines in time allocated to work in these cases for temperatures above 85°F.[8]

III. Decoupling Natural and Produced Amenities

The use of water intensive landscaping for mitigation of the urban heat island physically couples two features of a location. It is an example of how the production of one amenity can serve to create joint outputs. Increased evapotranspiration and shading from green landscaping can reduce the storage of heat and lessen the UHI. An anticipated byproduct of these types of mitigating responses is a reduction in the expenditures on electricity for cooling. This linkage implies analysts are unlikely to be able to construct a quasi-experiment that assigns temperatures in a way that is uncorrelated with landscape. Since the physical mechanisms that generate the UHI depend on the landscape, the two phenomena cannot be artificially separated. We also suggested reasons to believe that landscaping is likely an impure public good. For this reason it may influence housing prices at both a highly localized (parcel) level and a more diffuse (neighborhood) scale. This differential level for capitalization reflects the landscaping decisions of many neighbors that aggregate to create both neighborhood level

[8] Other studies have also offered support for their conclusions. For example, Connolly's [2008] analysis of rainfall and work and leisure is broadly consistent in the sense that labor in general is not affected by the weather. This finding was also true for Graff-Zivin and Neidell. The effect was under high temperatures for individuals likely to be working outside. Black et al.'s [2014] analysis of air pollution conditions on outdoor leisure activities using the ATUS between 2003 and 2010 appears to be broadly consistent. These authors include controls for temperature but do not report the specific estimates. Their findings suggest that controls for temperatures along with other fixed effects influence the ability to detect extensive margin adjustments to air pollution conditions. Finally Siikamaki [2009] used the ATUS as well as other time use surveys to consider trends in the time spent for outdoor recreation from 1965 to 2007.

amenities and microclimate effects that are likely to be noticeable at the relatively coarse scale of neighborhoods.[9]

Recovering a tradeoff measure for reducing nighttime temperatures requires that the analysis be capable of using temperature differences at multiple spatial scales to capture the effects of both spatially differentiated microclimates and any associated differences in landscaping. This task is especially challenging because the variables used to measure temperature and landscaping are likely to be correlated with other omitted variables at each spatial scale. Parcel-level benefits from green landscape may be correlated with unobserved neighborhood characteristics while gains associated with landscape features across broader spatial scales influencing neighborhood quality, such as access to local jogging or walking paths, are also liked to be correlated. In addition it is also important to recognize the possibility for temporal changes in unobservables due to urban expansion. Temperature, while perhaps not significantly varying at parcel and neighborhood spatial scales, may be correlated with evolving larger-scale features of an urbanizing landscape, particularly aspects of development density.

The potentially complex interplay between omitted unobservables and the multi-scalar nature of the effects of landscape and UHI creates challenges to the spatial fixed effects approaches often employed in hedonics. It particularly limits the ability to use relatively small-scale spatial fixed effects to absorb temporally stable omitted variables at or above this scale as these would absorb the variation in temperature needed for identification. Given this property, the analyst is faced with a tradeoff in selecting the scale of fixed effects. Consistent estimation of fine-level effects (e.g. effects of landscaping at or below the neighborhood level) might preclude identification of more widespread and slowly-varying spatial phenomena such as the UHI.

[9] There may also be some excludable benefits to the parcel-level microclimate of one's own landscape, e.g. Stone and Norman [2006]).

Abbott and Klaiber [2010; 2011] address this problem by recasting traditional cross-sectional hedonic data as a panel, where the panel is defined as transactions within discrete spatial "neighborhoods" (e.g., subdivisions, census units, etc.) and then proposing a spatial adaptation of the Hausman-Taylor panel data estimator (Hausman and Taylor [1981]). The Hausman-Taylor model combines elements of both random effects and fixed effects estimation for panel data using instrumental variables to correct for correlation between explanatory variables and spatially-defined random effects. To instrument for all variables that vary below the scale of the spatial effects, the model utilizes the within-transformation of variables to form instruments. For endogenous variables that lack "within" variation, these instruments are constructed using the within-panel means of a subset of the within-varying variables that are hypothesized to be exogenous. Our presentation of this model here closely parallels Abbott and Klaiber [2011] with a change that is especially relevant to our application. We augment the purely spatial definition of panels used in their application to include a temporal dimension, so that a panel is defined as the intersection of a given spatial zone with the sale year for the houses in our sample. This change allows our new framework to address the effects arising from time-varying omitted variables and, as we explain below, facilitates the estimation of temperature effects.

As with most hedonic regression models, the (natural log) of housing price P_{ijt} is hypothesized to be determined by a linear function of a series of home, neighborhood and area attributes

(1) $$P_{ijt} = \alpha_0 + \alpha_1 X_{ijt}^1 + \alpha_2 X_{ijt}^2 + \alpha_3 Z_{jt}^1 + \alpha_4 Z_{jt}^2 + \eta_{jt} + \epsilon_{ijt}$$

where the ijt subscript represents individual houses, spatial neighborhood, and time, respectively. Variables denoted by X are ijt specific and classified as either endogenous (superscript=1) or exogenous (superscript=2), while variables denoted by Z do not vary within the jt panel dimension and similarly can be either endogenous or exogenous. Unobserved random effects which vary over location and time are given by η_{jt} and ϵ_{ijt} is an idiosyncratic error. The endogeneity of X_{ijt}^1 is assumed to be of a particular form so that $Corr\left(X_{ijt}^1, \eta_{jt}\right) \neq 0$ but X_{ijt}^1 is exogenous with respect to the idiosyncratic error

ϵ_{ijt}.[10] As this specification suggests, the econometric challenge is to consistently estimate coefficients for the endogenous variables, X_{ijt}^1 and Z_{jt}^1, in the presence of omitted variables.

The process begins by first obtaining consistent estimates of α_0, α_1 and α_2 using the within estimator and computing the residuals. The within panel means of these residuals correspond to spatial/time fixed effects. Regressing these means on Z_{jt}^1 and Z_{jt}^2, using exogenous variables X_{ijt}^2 and Z_{jt}^2 as instruments, recovers initial estimates for α_3 and α_4. With estimates of all coefficients in hand, it is then possible to estimate the variance of the error components. These variance estimates are used to develop a random effects feasible GLS (FGLS) transformation on equation (1) as shown in equation (2)

(2) $$\tilde{P}_{ijt} = \alpha_0 \tilde{1}_{jt} + \alpha_1 \tilde{X}_{ijt}^1 + \alpha_2 \tilde{X}_{ijt}^2 + \alpha_3 \tilde{Z}_{jt}^1 + \alpha_4 \tilde{Z}_{jt}^2 + \tilde{\epsilon}_{ijt}$$

where $\tilde{1}_{jt}$ is a FGLS transformed column vector of ones. The final step is to develop an instrumental variables regression using the within-transformed variables, $\hat{X}_{ijt}^1$ and $\hat{X}_{ijt}^2$; the transformed non-within-varying exogenous variables, $\tilde{Z}_{jt}^2$; and the neighborhood means of within-varying exogenous variables $\bar{X}_{jt}^2$. Note that exogenous jt variables are instrumented by themselves while $\bar{X}_{jt}^2$ provides instruments for the endogenous jt variables. Identification rests on the ability to find a number of exogenous within-varying variables that equal or exceed the number of endogenous non within-varying variables, $\tilde{Z}_{jt}^1$.

For a valid instrumental variable estimator for equation (2) the within-panel means of these within-varying characteristics $\bar{X}_{jt}^2$ must be correlated with $\tilde{Z}_{jt}^1$ while also being uncorrelated with η_{jt}. We follow Abbott and Klaiber [2011] and construct a pseudo-Hausman test suggested by Wooldridge [2002] to test this hypothesis. A Wald test for this hypothesis compares the coefficient estimates for $X_{ijt}^2$from fixed and random effects estimates. It tests the null-hypothesis that the difference in the two sets of coefficients estimated under different maintained hypotheses is zero. Failure to reject this condition

[10] This is the standard assumption underlying the standard fixed effects estimation strategy in a spatial hedonic setting.

indicates that random effects and fixed effects estimates cannot be distinguished on statistical criteria, supporting the conclusion that the X_{ijt}^2 are uncorrelated with η_{jt}.[11]

While this description has assumed that the error correlations follow a random effects pattern, so that the transformed error in the FGLS equation (2) is spherical, this is not necessary for consistency of the coefficient estimates. To account for spatial and temporal correlation within panels as well as heteroskedasticity, we calculate cluster-robust standard errors using a nonparametric cluster bootstrap (Cameron, Gelbach and Miller [2008]), with clusters defined at the same scale as the random effects.

IV. Data

Our data consists of all single family residential transactions in Maricopa County (the county containing Phoenix and most of its MSA) between 1999 and 2005. Phoenix experienced rapid growth during this period. Our primary source of transactions data comes from the private data vendor, Dataquick, and is supplemented with data from the Maricopa County Assessor. These data contain a complete inventory of single family residential transactions as well as an extensive list of structural characteristics and lot size. After removing outliers and observations with missing information, we are left with a dataset containing 614,700 individual transactions. We further restrict the sample to areas containing a minimum of 5 transactions in each tract/year combination. This removes an additional 236 transactions that were primarily located a considerable distance outside the urban area. Our resulting dataset contains 614,464 individual transactions occurring over 630 Census 2000 tracts (Figure 1).

The Hausman-Taylor model requires a clear definition of the spatial and temporal scale of the random effects. Census 2000 tracts are used to define the spatial dimension of the random effect (the j dimension). These spatial effects are interacted with the year of sale (the t dimension) to define our

[11] To ensure robustness of the test to errors that fail to follow the random effects assumptions, we follow Wooldridge's suggestion and use a cluster-robust estimate of the covariance matrix in the Wald test.

random effects, yielding an unbalanced panel of 4,341 unique tract/year combinations. While varying in spatial size depending on population density, tracts provide a commonly used definition of a "neighborhood" – knitting together areas with similar observed and unobserved public goods while also allowing significant "between" variation across tracts to identify the coefficients of variables that vary at or above the tract level. To take account of the rapid increases in housing prices in Phoenix during our sample period, we normalize transactions prices to January 1998 dollars using the monthly Case-Shiller price index for Phoenix. We further convert these normalized prices to an annual rental rate using a value of 11% following Poterba [1991]. Summary statistics for prices as well as other structural characteristics including square footage, lot acreage, number of stories, number of bathrooms, age of house, number of rooms, and indicators for the presence of a garage and pool are shown in Table 1. Overall, the mean annualized Case-Shiller adjusted sales price in our sample is slightly over $16,349 in 1998 dollars, with a nominal sales value of $221,416. The typical home contains approximately 1,900 square feet, slightly over 2.5 bathrooms, and is situated on 0.20 acres. These summary features are consistent with the pattern of relatively dense (for detached housing) development of subdivisions in the area. We calculate a further set of parcel specific GIS attributes which consist of distances to the nearest highway and downtown Phoenix, as well as distances to and adjacency indicators for local parks, city parks, and subdivision provided open space following Abbott and Klaiber [2010].

Information on landscape characteristics is obtained from remote sensing data (Stefanov, Ramsey and Christensen 2001) which classified satellite imagery in the Phoenix area into 12 unique categories. Their classification system analyzed differences in reflectivity to assign one of 12 land cover types to 30x30 meter squares (rasters) covering our study area. The land cover types include cultivated vegetation, cultivated grass, vegetation, fluvial and lacustrine sediments (canals), water, undisturbed, disturbed soil with agricultural water rights, compacted soil, commercial/industrial, asphalt and concrete, mesic residential, and xeric residential. By comparing the land cover classification to aerial photography of residential lots, we chose to combine the categories cultivated vegetation, water, and mesic residential to form an "irrigated" classification where the remaining categories are considered "dry" or xeric. We overlaid classifications on GIS parcel maps, categorizing a parcel as irrigated based on the intersection of parcel centroids. Figure 2 provides an example of the parcel level classification of irrigated land cover. In addition to the parcel-level classification of landscaping, we created a subdivision-level measure of green landscaping to capture aspects of neighborhood landscaping that capitalize to all houses in the neighborhood.[12] For a subdivision to be characterized as mesic or "wet", at least 75% of the parcels in the subdivision must be identified as irrigated. This characterization results in a total of 261 wet subdivisions shown in Figure 3 with the remaining subdivisions containing a mix of irrigated and xeric landscaping.

Our final parcel-specific variable is elevation which was obtained from USGS digital elevation models. These provide precise measures of elevation as continuous raster files which are intersected with parcel centroids using GIS. Summary statistics for this variable are shown in table 1 showing that the mean elevation is 391 meters with a range from 259 meters to 969 meters. Phoenix is located in an alluvial plain, with elevations increasing to the north and south of downtown. The majority of higher elevation parcels are located at a considerable distance from downtown Phoenix and are associated with mountain outcroppings on the desert plain. We hypothesize that elevation provides considerable amenity value to households through improved views.

Tract-level temperature measures for July minimum temperatures are obtained from the PRISM database maintained by Oregon State University (http://www.prism.oregonstate.edu). These data are available monthly at a 4 kilometer resolution. We focus on July temperatures and nighttime minimum temperatures consistent with the focus of most UHI research. Since temperatures are unlikely to vary

[12] A subdivision is typically substantially smaller than either a Census block group or tract, with an average of 70 homes. Homes within a subdivision are often fairly homogenous, may share a number of local public goods and are often governed by a single home ownership association.

substantially within tracts, several steps are used to estimate tract July minimum temperature specific for each year of our transactions data. The first step is to obtain (using latitude and longitudes) the July minimum temperature associated with each parcel in our database for each year. We then attach to each parcel the nearest July low temperature to the year we observed a transaction for each house. For houses transacting from January through June we attach the previous year's July low temperature, and for houses transacting between July and December we attach the current year's temperature. Finally, we average over all transactions in each tract/year combination to form a spatially and temporally varying measure of temperature. Figure 4 shows the resulting temperature measures at the Census tract level for the year 2005. We use this annually updated measure of temperature under the assumption that current and potential renters will draw upon the most recent part of the historical record to form their expectations of a year's summer temperatures. We also assess the sensitivity of the model to this assumption. Between 1999 and 2005, the average nighttime minimum temperature across all tracts ranged from a low of 77.9 (F) degrees in 1999 to a high of 80.5 (F) degrees in 2003. This general increase in temperature is what would be expected from urban heat island effects associated with increased development. Our final set of within-panel invariant control variables includes Census 2000 demographics on age composition and race. Summary statistics for each of these variables are shown in Table 1.

V. Results

The Hausman-Taylor estimator requires that the variables influencing housing prices be partitioned into exogenous and (potentially) endogenous categories. Defining panels as Census tract/year combinations, we treat all of the within-panel invariant variables, except temperature, as exogenous. While all within-panel varying variables are instrumented using their "within" transformations, the strategy used in the case of temperature requires at least one of these variables to be assumed exogenous, allowing the within-panel means of these exogenous variables to provide the identifying variation for the effect of temperature. To meet this need we assume that distance to subdivision open space and elevation are exogenous, implying our estimation is over-identified by one degree of freedom. For these variables to function as instruments, they must be uncorrelated with the error and partially correlated with temperature. The relevance of proximity to subdivision open space stems from the effects on neighborhood density from open space provision. Increased provision of open space reduces development density, thereby reducing urban heat island effects. We follow Abbott and Klaiber's [2011] arguments for distance to subdivision open space as a valid instrument. Specifically, subdivision open space often serves an important role as "retention basins" for urban storm water runoff. It also meets mandates by zoning apart from endogenous market considerations. Thus, it satisfies the needs for being correlated but not jointly determined with temperature. The relevance of elevation as an instrument is well-established in the UHI literature. Elevation is likely to be exogenous due to the geological nature of its "provision" as well as the specific structure of the Phoenix landscape. Downtown Phoenix is located at the bottom of a "bowl", with elevation slowly increasing (at different rates depending on direction) with distance from the city center. This gradual elevation change is not readily apparent and as such is likely to be uncorrelated with unobservable characteristics, particularly after controlling for Census demographics.[13]

Before presenting our preferred estimates we first present three alternatives to the Hausman-Taylor model in Table 2: naïve OLS, random effects (RE) with effects defined for tract/year combinations, and fixed effects (FE) using tract effects. When these estimates are compared with those using our adaptation of the Hausman-Taylor logic each set serves to highlight the importance of our identification strategy and the influence of endogeneity in estimates developed with methods that do not take

[13] There are a handful of developed mountainous outcroppings that offer exceptions to this story of gradual elevation change. Homes located on these outcroppings represent a small fraction of sales, but do tend to possess views and more luxurious amenities that are not captured in the available housing characteristics.

account of its role for several key determinants of housing prices in this market. The OLS estimator exploits both within and between panel variation in the independent variables. However, it ignores the potential for correlation between omitted spatial and temporal effects and the dependent variables and may therefore exhibit omitted variables bias at all spatial scales. The random effects estimator efficiently accounts for the contribution of within and between variation in its estimates, resulting in estimates similar to those using the within estimator for datasets with long panels and with a relatively high variance for the unobserved spatial and temporal heterogeneity in the random effects (Abbott and Klaiber [2011]). However, like OLS, RE estimates are not consistent –particularly for variables with little or no within-panel variation, such as tract-level attributes. The FE estimates utilize only within-panel variation. Because our measure of July minimum temperature varies by tract and year, we are unable to recover estimates of the marginal effect of temperature using tract/year fixed effects. Therefore, we consolidate fixed effects to the tract level, utilizing only the inter-annual variation in temperature within each tract for identification.

In general, the RE estimates are comparable to the FE estimates for variables with substantial within-panel variation. The value of a green lot is consistent across all three specifications, yielding approximately a 1% premium for conversion to green landscaping. However, moving from OLS to RE reduces by about one-half the magnitude of the estimated effect of subdivision-wide green landscaping – from a 22% premium in the OLS specification to about 12% under RE. Comparing the estimates for July minimum temperature, we find that a 1(F) degree increase in tract level nighttime temperatures decreases rental values by approximately 2% according to the OLS estimate and 3.2% according to RE. The FE approach of discarding between-tract variation in temperatures and relying exclusively on temporal variation in temperatures within tracts yields the counter intuitive finding that a 1(F) degree rise in nighttime temperatures *increases* rental values by 3.9%. This clear difference in the implications of temperature suggests that retaining between-tract variation in temperature is an important source of variation. Nonetheless, the RE model may be biased if the tract/year effects are correlated with model covariates. Temperature, in particular, varies across both spatial and temporal dimensions. As a result, it is possible that it is correlated with the latent spatial and temporal features of the landscape, such as development density.

To address the concerns about consistency at all scales, we turn to the Hausman-Taylor estimator. This approach instruments for temperature using the within-tract annual means of elevation and distance to subdivision open space. Table 3 presents information supporting the relevance of these instruments. The correlations between temperature and the within-tract means of elevation and distance to subdivision open space are -0.31 and 0.35 respectively .The two instruments are not themselves highly correlated, with a correlation of -0.17. The pseudo-Hausman tests fail to reject the null hypothesis that the instruments are individually and jointly exogenous.

The results for the Hausman-Taylor model are shown in Table 4. The variables are grouped according to whether they are assumed to be endogenous or exogenous and whether they vary within the tract/year panels or between them. Focusing on the estimates using PRISM temperature data, we first examine the results for the within-varying exogenous variables, whose means serve as instruments for temperature. The estimates correspond closely to those using both the naïve OLS and the random effects models, suggesting the assumption of exogeneity is reasonable. They are also statistically significant within *p*-values of 0.01 or lower. A 100m increase in elevation results in an estimated price increase of 8.2% or about $112 more in monthly rents while a 1 mile reduction in distance to subdivision open space increases rental values by 4.1%.

The second category of variables includes the endogenous, within-varying characteristics, consisting of: structural housing characteristics, measures of distance and adjacency with respect to parks, highways, and the central business district, as well as block group summary measures for land use and landscape characterization. We find the expected signs for structural characteristics including positive and significant signs on the coefficients for square footage, acreage, and baths. Similarly, the coefficients for the distance measures exhibit signs consistent with expectations and previous work (Abbott and Klaiber [2010]).[14] Turning to landscape characteristics, we find a significant but small premium of 1% for green landscaping at the parcel level but find a much larger premium of approximately 11% for living in a green subdivision.

The third category of variables includes panel-invariant variables that do not require the development of instruments. While these variables are treated as exogenous, they are primarily included to control for observable features of the tract-level "neighborhoods", reducing the scope for omitted variables bias. We anticipated that including these variables would enhance the validity of the instruments for tract-level temperature. Since they serve a role as controls we do not attempt to interpret the estimated coefficients for these variables. Also included within this category are dummy variables for each year, which show a trend of "real" price appreciation over our sample period even after deflating prices using the Case-Shiller index.

The HT estimate for July minimum temperature yields a negative and statistically significant coefficient of -0.041, indicating that households are willing to pay approximately 4.1% more to live in an area with a 1°F reduction in nighttime temperatures. This estimate is appreciably larger than both the OLS estimate and the RE estimate (Table 2). This aversion to heat island effects corresponds to a monthly willingness to pay of approximately $56 to avoid a 1 degree increase in temperature using the mean monthly rental price of $1,362.

These estimates provide direct confirmation of a feedback loop from UHI impacts associated with urbanization. They imply that households recognize the relatively higher nighttime temperatures and sort in neighborhoods to reduce the size of the UHI's effects. These estimates take explicit account

[14] Our model specifications were selected to be as close as feasible to this previous work. The focus of the earlier work was subdivision open space in relation to other, more open access, open space areas. As a result the spatial unit for the panel is different.

of green landscape as a mitigating factor. They exploit the spatial and temporal variation in prices, landscape and temperature, as well as develop instruments to account for the endogenously determined landscape and temperature values for specific parcels. To our knowledge, this analysis is the first example of how market mechanisms can serve the role of signaling changes in urban climate and ecosystems in response to urbanization and in turn confirming people's responses to them.

We also evaluated the robustness of our results by considering a range of alternative specification assumptions. To examine whether our estimates are sensitive to alternative measures of summer minimum temperatures we replace the PRISM estimates of mean minimum July temperature with inverse-distance weighted interpolations of the July mean minimum temperature from roughly 20 active NOAA weather stations located in Maricopa County (see the estimates in Table 4). The estimates of the temperature marginal effect are very similar in magnitude regardless of how temperature is measured – -.041 relative to -.045 – with the estimates of other parameters remaining essentially unchanged.

As noted earlier, our temperature measure is based on the assumption that the relevant metric is the minimum temperature in the most recent July. This specification assumes that the expectations of renters update in a myopically adaptive way that discards information contained in previous years' temperatures. It also implies that inter-annual variation within tracts, as well as differences in temperature across tracts, play a role in the identification of the effects of the urban heat island. To assess the sensitivity of our estimates to this aspect of our specification, we replaced the minimum July temperature with averages of the minimum July temperature over the previous two years. The resulting estimate is virtually indistinguishable in sign and significance from the original HT estimate (Table 5). Alternative specifications, using an even larger smoothing window (and not reported here) show little change in the estimated marginal effects of temperature. However, as the smoothing of the temperature measure increases and approaches the tract level sample mean, the standard errors do increase so that we cannot reject the null hypothesis of no association. These analyses suggest that while cross-sectional differences across tracts in temperature are ultimately capitalized into home prices, retaining temporal variation is essential to the process of developing precise estimates.

Finally, we assessed whether our results were sensitive to the choice of statistical summary measure for temperature. The urban heat island is often characterized in terms of a variation on an order statistic, namely the nighttime minimum temperatures. This logic for this selection is likely motivated by the assumption that weekday exposure to neighborhood microclimate for many working homeowners will be in nighttime hours. In addition, while air conditioning is pervasive among private homes, the ability to maintain cool sleeping temperatures depends on outside conditions and would therefore be another reason for the focus on nighttime temperatures. Despite these arguments there is no obvious, *a priori* metric that encompasses all the relevant dimensions of neighborhood microclimate. Daytime maximum temperatures may be more salient for outdoor activities on weekends but would not necessarily be confined to areas around the house. Furthermore, to the extent that centralized air conditioning with a thermostat is used to avert the effects of extreme summertime heat, both minimum and maximum temperature are potentially relevant. Table 5 reports estimates using the July *maximum* (daytime) temperature and shows that the marginal effect is indistinguishable from when the minimum temperature is used. When both minimum and maximum temperature are included as endogenous regressors (not shown)[15], both coefficients attenuate in absolute value and become insignificant. Altogether, the evidence suggests that the estimated effects of maximum or minimum temperatures relate to a shared common component of temperature reflected in both measures (the two measures have a correlation of 0.45), rather than minimum or maximum temperature *per se*.

To provide some context for our estimated marginal willingness to pay for a reduction in temperature, it is helpful to consider how it compares to estimates of the energy cost savings from

[15] This leads to a just-identified model relative to the over-identified models using one temperature variable.

reduced air conditioning costs. Estimates for this saving depend on a wide array of factors such as the albedo of building surfaces, the quality of insulation, the size and external surface area of the building, the efficiency of air conditioning, thermostat settings, and the exact nature of the change in the daily outside temperature profile. We abstract from these details and draw upon the simulation model of Matsuura [1995] to provide an approximate gauge of the effect. His analysis considers a 1 degree (F) increase in mean outside temperature. This would increase the average daily energy load for a two-story, 1640 ft^2 townhouse (slightly smaller than the mean detached home in our sample) in Phoenix kept at a constant comfortable temperature by approximately 7.5kWh/day or 232.5 kWh per month. Translating this energy use into monthly utility costs depends on the pricing plan chosen (e.g., one that charges for peak and off-peak usage vs. a flat rate) and the baseline usage (since many utilities use increasing block rates). However, using 2014 summer[16] seasonal rates from Arizona Public Service's "standard" plan for homes in the 801-3000 kWh monthly usage bracket, the marginal cost of a kWh is $0.162. Using this composite of assumptions, this analysis results in increased utility costs from a 1 degree temperature increase of approximately $38/month, which converted to 1998 dollars using the urban consumers CPI amounts to $26.[17] This is about half of our estimate of the monthly willingness to pay to avoid one degree temperature increase of $56. This lower value is reasonable since adjustments to indoor conditions do not offer a perfect substitute for cooler outdoor conditions. The ability to use outdoor space in the evening is affected by nighttime conditions whereas air conditioning addresses only the indoor living environment.

VI. Discussion

[16] Almost all energy usage from increased mean temperatures would occur in summer months, with negligible energy savings from less heating in the (very mild) Phoenix winters (Matsuura [1995]).

[17] The CPI component for energy in 1998 was 161.6 using a base of 1980-82. For January 2014 it was 233.9.

Ecologists have provided detailed evidence, due in large part to the national LTER research program, of how urban ecosystems and the services they provide to people are affected by both development density and its form. Ecologists have also argued that we should expect a feedback loop whereby changes in these services affect people, causing them to adopt mitigation and adaptation strategies which can in turn further alter urban ecosystems. This conjecture, while plausible, has not been convincingly verified to date. The links from urbanization and increased development density to the temperature outcomes of the UHI are well known. We provide the first evidence – using the "fingerprints" revealed by market activity in a differentiated housing market – that there is a corresponding response from people. Households' choices of where to live and the types of landscape to maintain provide a part of the hypothesized feedback loop. In metropolitan Phoenix one observes neighborhoods where homeowners modify landscapes, water treatments, and design features of their homes to adapt to and locally mitigate summer temperatures. Developers plan subdivisions to incorporate landscape, open space, and building envelopes to reduce temperatures. The housing market signals the importance of reduced urban nighttime temperatures and thereby provides incentives for the adoption of means to achieve this end. The nature of this feedback loop also suggests why efforts to reduce outdoor water use may not be as successful as hoped by local water providers. Landscape amenities requiring water command premiums that are only partially replaced by attractive xeric alternatives. While natural desert landscapes may provide many aesthetic benefits, their use of heat-absorbing rock and low evapotranspiration do not facilitate temperature reductions and may actually increase nighttime temperatures.

Our results demonstrate that green landscaping generates substantial benefits to homeowners, both for its direct benefits and its indirect effects as an input for the cooling of the surrounding microclimate. As development in arid areas such as the U.S. Sun Belt continues and as climate change and the urban heat island effects of development progress, one of the effects may well be that quantities of water required to sustain mitigation through green landscaping are likely to increase even as the social opportunity cost of the water rises contemporaneously.

A full analysis of the tradeoffs inherent in evaluating the importance of continued efforts at conservation of outdoor water use requires a comparison of the value of water in its use as an input (i.e. the value of its marginal product) to green vegetation and temperature moderation compared to the value of water in alternative uses. This type of assessment requires the integration of valuation techniques – such as the hedonic price regression estimated here – for the final valued "services" or "outputs" with knowledge of the underlying production functions linking the use of water inputs to the valued amenities.[18] It also requires information on other strategies for mitigation to reduce the effects of increases in outdoor temperatures. It is possible to develop the conceptual logic that links the equilibrium first-stage hedonic approaches to biophysical production relations for green landscaping and temperature. However, this approach is less suitable for considering the endogenous feedbacks between water use, land cover, temperature, the patterns of development, and welfare that are likely to result over long time scales or as a result of significant land use or water policy interventions.

Providing *ex ante* analysis of the tradeoffs likely to be associated with alternative policy instruments for mitigation and adaptation requires the integration of biophysical "production functions" with structural economic models of location choices by households and the spatial supply decisions of developers.[19] While complex and data intensive, we argue that this sort of structural, interdisciplinary modeling is essential to making the transition from *understanding* present tradeoffs to *anticipating* the effects of policy interventions in complex, dynamic urban environments that have embedded feedbacks that arise from *both* ecological and economic processes.

[18] Abbott and Klaiber [2013] provide an example of this approach where the linkage between the use of water inputs and the valued amenity is relatively transparent.
[19] See Kuminoff et al. [2013] for a review of this literature and Klaiber and Phaneuf [2010] for one of the first efforts to consider the housing supply response with a spatially delineated context.

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Table 1: Summary statistics (N=614,464)

	Mean	Std Dev	Min	Max		Mean	Std Dev	Min	Max
Sale Price (Annual, 1998 dollars)	16349	18990	739	973384	Distance to highway (miles)	5.0607	4.0662	0.0003	24.4125
Sale Price (Nominal)	221416	256130	17000	10000000	Distance to highway sq	42.1450	59.6745	0.0000	595.9692
Elevation (100s of meters)	3.9163	0.7191	2.5893	9.6962	Distance to local park (miles)	0.9368	0.8255	0.0031	14.4390
Distance to subd. open space (miles)	0.3639	0.4596	0.0059	7.0004	Distance to city park (miles)	5.2039	3.8175	0.0286	29.8113
Summer Min Temp (PRISM)	78.7513	1.3130	74.6330	83.4535	Adjacent subd. open space (0/1)	0.0521	0.2221		
Summer Min Temp (Monitor)	79.3953	1.2560	73.0608	84.9613	Adjacent city park (0/1)	0.0003	0.0186		
Summer Max Temp (PRISM)	106.0373	1.5571	100.2242	110.3890	Adjacent local park (0/1)	0.0024	0.0486		
Green landscape (0/1)	0.0933	0.2908			Local park area (within 1500 ft)	1.5616	5.9547	0.0000	127.5382
Green subdivision (0/1)	0.0937	0.1309			Subd open space area (within 1500 ft)	9.1060	16.3581	0.0000	284.4212
Square feet (100s)	19.2619	7.3236	6.0000	60.0000	% Residential (block group)	0.5303	0.2671	0.0010	1.0000
Acres	0.2086	0.1853	0.0500	13.9374	% Agricultural (block group)	0.0501	0.1003	0.0000	0.6189
Stories	1.1963	0.3974	1.0000	4.0000	% Vacant (block group)	0.2542	0.2245	0.0000	0.9586
Bathrooms	2.6214	0.8366	0.5000	6.0000	% Commercial (block group)	0.0724	0.0914	0.0000	0.8027
Age	14.3327	15.6857	1.0000	86.0000	% Hispanic	0.1837	0.1835	0.0000	0.9605
Garage (0/1)	0.9578	0.2010			% Black	0.0254	0.0429	0.0000	0.6598
Pool (0/1)	0.3301	0.4702			% Children	0.2743	0.0950	0.0000	0.4678
Rooms	6.6369	1.5570	3.0000	19.0000	% Age 18-35	0.2275	0.0949	0.0000	0.6500
Square feet sq	424.6561	364.6836	36.0000	3600.0000	% Age 35-55	0.2885	0.0836	0.0174	0.4751
Acres sq	0.0779	0.5839	0.0025	194.2523	Year = 1999	0.1249			
Age sq	451.4647	814.2542	1.0000	7396.0000	Year = 2001	0.1187			
Adjacent to rail (0/1)	0.0021	0.0459			Year = 2002	0.1252			
Adjacent to canal (0/1)	0.0098	0.0986			Year = 2003	0.1415			
Adjacent to school (0/1)	0.0047	0.0685			Year = 2004	0.1854			
Distance to CBD (miles)	16.0656	6.2910	0.5029	38.8356	Year = 2005	0.1964			
Distance to CBD sq	297.6804	204.9631	0.2530	1508.2010					

Table 2: Comparison of OLS, random effects and fixed effects estimators.

	OLS	RE	FE
Elevation	0.114***	0.0877***	0.0861*
	(0.00739)	(0.0135)	(0.0457)
Distance to subd. open space	-0.0200***	-0.0342***	-0.0340***
	(0.00687)	(0.00596)	(0.0109)
Summer min temperature (PRISM)	-0.0208***	-0.0323***	0.0394***
	(0.00506)	(0.00408)	(0.0140)
Green landscape (0/1)	0.0106***	0.0101***	0.0100***
	(0.00157)	(0.00142)	(0.00167)
Green subdivision (0/1)	0.222***	0.119***	0.110***
	(0.0166)	(0.0100)	(0.0154)
Square feet (100s)	0.0560***	0.0523***	0.0517***
	(0.00141)	(0.00111)	(0.00187)
Acres	0.299***	0.333***	0.325***
	(0.0241)	(0.0189)	(0.0288)
Stories	-0.107***	-0.0826***	-0.0813***
	(0.00544)	(0.00354)	(0.00499)
Bathrooms	0.0736***	0.0487***	0.0478***
	(0.00380)	(0.00317)	(0.00441)
Age	-0.0120***	-0.00973***	-0.00921***
	(0.000582)	(0.000423)	(0.000665)
Garage (0/1)	0.0667***	0.0539***	0.0495***
	(0.00431)	(0.00329)	(0.00479)
Pool (0/1)	0.0593***	0.0545***	0.0545***
	(0.00163)	(0.00129)	(0.00195)
Rooms	-0.0215***	-0.0157***	-0.0160***
	(0.00185)	(0.00139)	(0.00233)
Square feet sq	-0.000424***	-0.000396***	-0.000385***
	(2.09e-05)	(1.50e-05)	(2.66e-05)
Acres sq	-0.0311***	-0.0359***	-0.0355***
	(0.00430)	(0.00466)	(0.00678)
Age sq	0.000139***	8.09e-05***	6.91e-05***
	(8.05e-06)	(6.64e-06)	(1.02e-05)
Adjacent to rail	0.0379	-0.0110	-0.0148
	(0.0280)	(0.0227)	(0.0244)
Adjacent to canal	0.0108*	-0.00676	-0.00827
	(0.00628)	(0.00549)	(0.00774)
Adjacent to school	-0.00505	-0.00627	-0.00194
	(0.0101)	(0.0110)	(0.00774)
Distance to CBD	0.0587***	0.0615***	0.0655***
	(0.0108)	(0.0120)	(0.0161)
Distance to CBD sq	-0.00160***	-0.00158***	-0.00167***
	(0.000280)	(0.000258)	(0.000371)
Distance to highway	0.00683	0.00355	0.00692
	(0.00657)	(0.00624)	(0.0132)
Distance to highway sq	-7.55e-05	-0.000367	-0.000372
	(0.000690)	(0.000600)	(0.00113)
Distance to local park	0.00296	0.00581	0.00861
	(0.00995)	(0.00959)	(0.00876)
Distance to city park	-0.00953**	-0.0107***	-0.0138**
	(0.00426)	(0.00385)	(0.00617)
Adjacent subd. open space	0.0322***	0.0375***	0.0373***
	(0.00436)	(0.00366)	(0.00660)
Adjacent city park	-0.0207	-0.0225	-0.0256
	(0.0300)	(0.0269)	(0.0335)
Panel dimension	Tract-x-Year	Tract-x-Year	Tract
Observations	614,464	614,464	614,464
R-squared			

	OLS	RE	FE
Adjacent local park	0.0207*	0.0141*	0.0207**
	(0.0111)	(0.00853)	(0.0104)
Local park area (1500 ft)	-0.000344**	-0.000132	-0.000109
	(0.000173)	(0.000153)	(0.000180)
Subd open space area (1500 f	0.000486***	0.000497***	0.000375*
	(0.000132)	(0.000115)	(0.000204)
% Residential (block group)	0.0135	0.0614***	0.0545***
	(0.0165)	(0.0102)	(0.0182)
% Agricultural (block group)	-0.102*	-0.0314	0.00604
	(0.0557)	(0.0391)	(0.0427)
% Vacant (block group)	0.0372*	0.0900***	0.0864***
	(0.0195)	(0.0252)	(0.0290)
% Commercial (block group)	0.0350	0.0894***	0.0764**
	(0.0325)	(0.0172)	(0.0352)
Distance to CBD	-0.0752***	-0.0992***	
	(0.0103)	(0.0123)	
Distance to CBD sq	0.00150***	0.00194***	
	(0.000278)	(0.000264)	
Distance to highway	-0.00385	0.0110	
	(0.00800)	(0.00696)	
Distance to highway sq	0.000741	0.000650	
	(0.000862)	(0.000687)	
Distance to regional park	-0.00386***	-0.00357***	
	(0.00146)	(0.00125)	
Distance to city park	0.0201***	0.0222***	
	(0.00419)	(0.00402)	
Distance to local park	-0.0236*	-0.0175	
	(0.0121)	(0.0126)	
% Hispanic	-0.415***	-0.503***	
	(0.0338)	(0.0249)	
% Black	-0.413***	-0.827***	
	(0.0765)	(0.0550)	
% Children	-0.254***	-0.274***	
	(0.0433)	(0.0454)	
% Age 18-35	-0.0321	0.0621*	
	(0.0548)	(0.0346)	
% Age 35-55	0.355***	0.483***	
	(0.0528)	(0.0472)	
Year = 1999	-0.00805	-0.00999	-0.000235
	(0.00790)	(0.00771)	(0.00369)
Year = 2001	0.0377***	0.0514***	-0.0106
	(0.0101)	(0.00873)	(0.0122)
Year = 2002	0.0328***	0.0678***	-0.0396**
	(0.0105)	(0.00914)	(0.0200)
Year = 2003	0.0801***	0.117***	-0.0546*
	(0.0146)	(0.0121)	(0.0318)
Year = 2004	0.0543***	0.0767***	-0.0180
	(0.0132)	(0.00981)	(0.0169)
Year = 2005	0.00966	0.0363***	-0.0164
	(0.0116)	(0.00850)	(0.0110)
Constant	10.10***	11.23***	4.751***
	(0.438)	(0.355)	(1.160)

Year by tract clustered robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Correlations between minimum July temperature and candidate instruments and pseudo-Hausman tests of instrument validity

Pseudo-Hasuman test for exogeneity		Correlation w/
Variable	p value	Temperature
Elevation	0.8176	-0.308
Dist to subd open space	0.7454	0.351
Joint test	0.9254	

Table 4: Hausman-Taylor estimates

	Temperature Specification	
	PRISM	Monitor (IDW)
Within Panel Exogenous		
Elevation	0.0817***	0.0815***
	(0.0187)	(0.0188)
Distance to subd. open space	-0.0359***	-0.0360***
	(0.00712)	(0.00707)
Between Panel Endogenous		
Summer min temperature	-0.0410**	-0.0447**
	(0.0179)	(0.0196)
Within-Panel Endogenous		
Green landscape (0/1)	0.00999***	0.00999***
	(0.00146)	(0.00146)
Green subdivision (0/1)	0.109***	0.109***
	(0.01000)	(0.01000)
Square feet (100s)	0.0520***	0.0520***
	(0.00111)	(0.00111)
Acres	0.338***	0.339***
	(0.0215)	(0.0215)
Stories	-0.0811***	-0.0811***
	(0.00367)	(0.00367)
Bathrooms	0.0475***	0.0475***
	(0.00311)	(0.00311)
Age	-0.00955***	-0.00954***
	(0.000440)	(0.000440)
Garage (0/1)	0.0513***	0.0513***
	(0.00340)	(0.00340)
Pool (0/1)	0.0543***	0.0543***
	(0.00130)	(0.00130)
Rooms	-0.0155***	-0.0155***
	(0.00138)	(0.00138)
Square feet sq	-0.000394***	-0.000394***
	(1.46e-05)	(1.46e-05)
Acres sq	-0.0366***	-0.0366***
	(0.00610)	(0.00610)
Age sq	7.47e-05***	7.46e-05***
	(7.01e-06)	(7.01e-06)
Adjacent to rail	-0.0139	-0.0139
	(0.0238)	(0.0238)
Adjacent to canal	-0.00826	-0.00825
	(0.00530)	(0.00530)
Adjacent to school	-0.00636	-0.00637
	(0.0109)	(0.0109)
Distance to CBD	0.0617***	0.0617***
	(0.0109)	(0.0109)
Distance to CBD sq	-0.00156***	-0.00156***
	(0.000240)	(0.000240)
Distance to highway	0.00391	0.00392
	(0.00707)	(0.00707)
Distance to highway sq	-0.000402	-0.000403
	(0.000684)	(0.000684)
Distance to local park	0.00590	0.00591
	(0.00976)	(0.00976)
Distance to city park	-0.0111***	-0.0111***
	(0.00378)	(0.00378)
Adjacent subd. open space	0.0376***	0.0376***
	(0.00364)	(0.00364)
Adjacent city park	-0.0237	-0.0237
	(0.0273)	(0.0273)
Adjacent local park	0.0134	0.0134
	(0.00851)	(0.00851)
Local park area (1500 ft)	-0.000131	-0.000131
	(0.000157)	(0.000157)
Subd open space area (1500 ft)	0.000497***	0.000496***
	(0.000120)	(0.000120)
% Residential (block group)	0.0624***	0.0622***
	(0.0103)	(0.0103)
% Agricultural (block group)	-0.0251	-0.0252
	(0.0435)	(0.0436)
% Vacant (block group)	0.0935***	0.0934***
	(0.0274)	(0.0274)
% Commercial (block group)	0.0895***	0.0896***
	(0.0195)	(0.0195)
Between Panel Exogenous		
Distance to CBD	-0.111***	-0.106***
	(0.0123)	(0.0121)
Distance to CBD sq	0.00229***	0.00212***
	(0.000266)	(0.000266)
Distance to highway	0.00597	0.00348
	(0.00870)	(0.00824)
Distance to highway sq	0.000986	0.000960
	(0.000790)	(0.000794)
Distance to regional park	-0.00384**	0.00106
	(0.00177)	(0.00136)
Distance to city park	0.0205***	0.0225***
	(0.00439)	(0.00407)
Distance to local park	-0.0277**	-0.0315**
	(0.0135)	(0.0131)
% Hispanic	-0.566***	-0.583***
	(0.0400)	(0.0449)
% Black	-0.802***	-0.877***
	(0.0614)	(0.0813)
% Children	-0.225***	-0.257***
	(0.0463)	(0.0520)
% Age 18-35	0.0101	0.0384
	(0.0398)	(0.0476)
% Age 35-55	0.401***	0.379***
	(0.0455)	(0.0487)
Year = 1999	-0.0210**	-0.0165**
	(0.00826)	(0.00798)
Year = 2001	0.0436***	0.0460***
	(0.0165)	(0.0175)
Year = 2002	0.0598**	0.0629**
	(0.0243)	(0.0254)
Year = 2003	0.121***	0.124***
	(0.0424)	(0.0438)
Year = 2004	0.0753***	0.108***
	(0.0264)	(0.0400)
Year = 2005	0.0253*	0.0544**
	(0.0149)	(0.0258)
Constant	12.10***	12.37***
	(1.487)	(1.621)
Panel Dimension	Tract-x-Year	Tract-x-Year
Observations	614,464	614,464
Number of year_spatial_id	4,341	4,341

Clustered bootstrap standard errors in parentheses (k=200)
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Hausman-Taylor estimates using alternative specifications of tract-level temperatures

	Temperature Specification	
	Two Year Avg	Max Temperature
Within Panel Exogenous		
Elevation	0.0817***	0.0816***
	(0.00233)	(0.0187)
Distance to subd. open space	-0.0359***	-0.0359***
	(0.00208)	(0.00709)
Between Panel Endogenous		
Summer min temp (2 yr avg)	-0.0399***	
	(0.0120)	
Summer max temp		-0.0404**
		(0.0176)
Within-Panel Endogenous		
Green landscape (0/1)	0.00999***	0.00999***
	(0.00122)	(0.00146)
Green subdivision (0/1)	0.109***	0.109***
	(0.00384)	(0.01000)
Square feet (100s)	0.0520***	0.0520***
	(0.000264)	(0.00111)
Acres	0.338***	0.339***
	(0.00358)	(0.0215)
Stories	-0.0811***	-0.0811***
	(0.00103)	(0.00367)
Bathrooms	0.0475***	0.0475***
	(0.000875)	(0.00311)
Age	-0.00955***	-0.00954***
	(0.000113)	(0.000440)
Garage (0/1)	0.0513***	0.0513***
	(0.00173)	(0.00340)
Pool (0/1)	0.0543***	0.0543***
	(0.000774)	(0.00130)
Rooms	-0.0155***	-0.0155***
	(0.000419)	(0.00138)
Square feet sq	-0.000394***	-0.000394***
	(4.34e-06)	(1.46e-05)
Acres sq	-0.0366***	-0.0366***
	(0.000853)	(0.00610)
Age sq	7.47e-05***	7.46e-05***
	(1.99e-06)	(7.01e-06)
Adjacent to rail	-0.0139*	-0.0139
	(0.00712)	(0.0238)
Adjacent to canal	-0.00826**	-0.00826
	(0.00330)	(0.00530)
Adjacent to school	-0.00636	-0.00636
	(0.00465)	(0.0109)
Distance to CBD	0.0617***	0.0618***
	(0.00157)	(0.0109)
Distance to CBD sq	-0.00156***	-0.00156***
	(3.67e-05)	(0.000240)
Distance to highway	0.00391***	0.00392
	(0.000973)	(0.00707)
Distance to highway sq	-0.000402***	-0.000403
	(5.47e-05)	(0.000684)
Distance to local park	0.00590***	0.00590
	(0.000807)	(0.00976)
Distance to city park	-0.0111***	-0.0111***
	(0.000593)	(0.00378)
Adjacent subd. open space	0.0376***	0.0376***
	(0.00154)	(0.00364)
Adjacent city park	-0.0237	-0.0237
	(0.0171)	(0.0273)
Adjacent local park	0.0134**	0.0134
	(0.00659)	(0.00851)
Local park area (1500 ft)	-0.000131**	-0.000131
	(5.94e-05)	(0.000157)
Subd open space area (1500 f	0.000497***	0.000497***
	(2.93e-05)	(0.000120)
% Residential (block group)	0.0624***	0.0623***
	(0.00469)	(0.0103)
% Agricultural (block group)	-0.0251***	-0.0251
	(0.00880)	(0.0436)
% Vacant (block group)	0.0935***	0.0934***
	(0.00589)	(0.0274)
% Commercial (block group)	0.0895***	0.0896***
	(0.00696)	(0.0195)
Between Panel Exogenous		
Distance to CBD	-0.112***	-0.0886***
	(0.00482)	(0.0141)
Distance to CBD sq	0.00232***	0.00176***
	(0.000126)	(0.000324)
Distance to highway	0.00594	0.00508
	(0.00401)	(0.00844)
Distance to highway sq	0.000981***	0.000729
	(0.000276)	(0.000827)
Distance to regional park	-0.00374**	-0.000384
	(0.00154)	(0.00110)
Distance to city park	0.0205***	0.0252***
	(0.00176)	(0.00393)
Distance to local park	-0.0278***	-0.0189
	(0.00939)	(0.0140)
% Hispanic	-0.570***	-0.438***
	(0.0374)	(0.0530)
% Black	-0.808***	-0.701***
	(0.0740)	(0.0585)
% Children	-0.222***	-0.273***
	(0.0634)	(0.0517)
% Age 18-35	0.0104	-0.0158
	(0.0504)	(0.0356)
% Age 35-55	0.396***	0.483***
	(0.0690)	(0.0509)
Year = 1999	-0.0374***	0.00361
	(0.0142)	(0.0109)
Year = 2001	0.0278*	0.0682***
	(0.0146)	(0.0261)
Year = 2002	0.0524***	0.0652**
	(0.0193)	(0.0261)
Year = 2003	0.0997***	0.157***
	(0.0268)	(0.0575)
Year = 2004	0.0958***	0.136***
	(0.0276)	(0.0514)
Year = 2005	0.0460**	0.123**
	(0.0199)	(0.0540)
Constant	12.02***	12.84***
	(0.967)	(1.809)
Panel Dimension	Tract-x-Year	Tract-x-Year
Observations	614,464	614,464
Number of year_spatial_id	4,341	4,341

Clustered bootstrap standard errors in parentheses (k=200)
*** p<0.01, ** p<0.05, * p<0.1

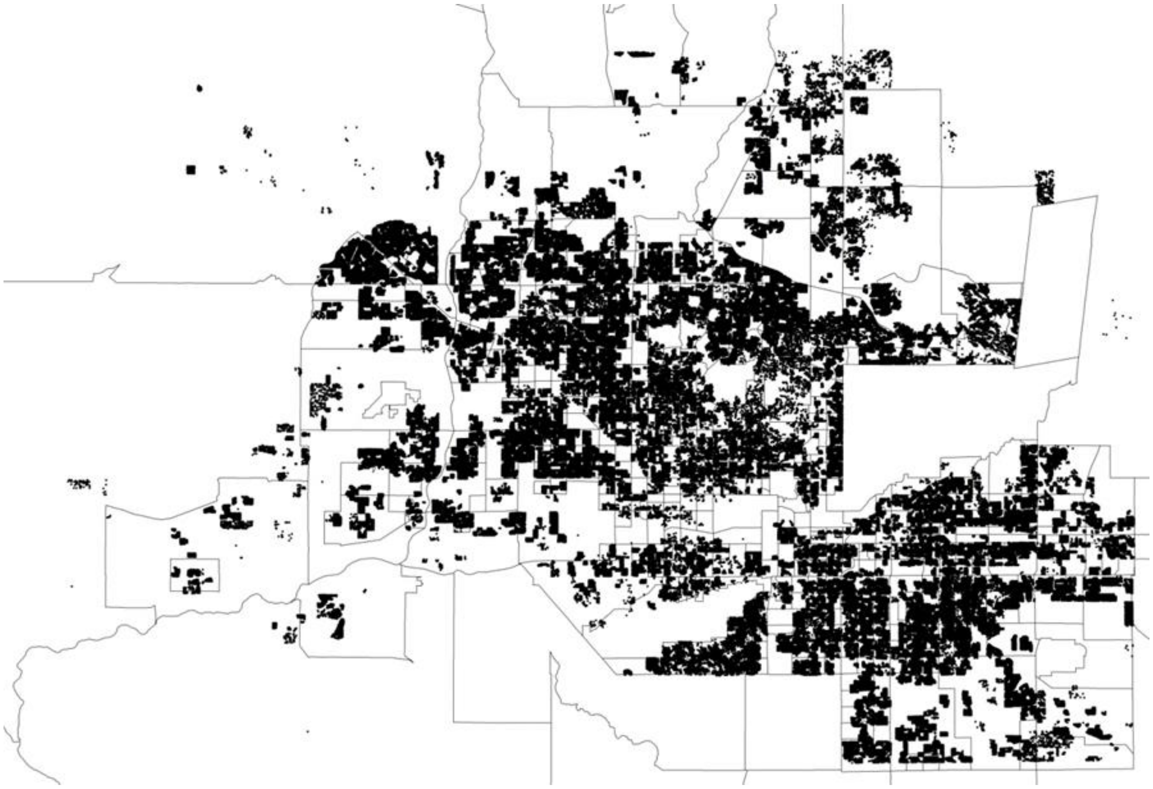

Figure 1. Transactions with 2000 Census tracts

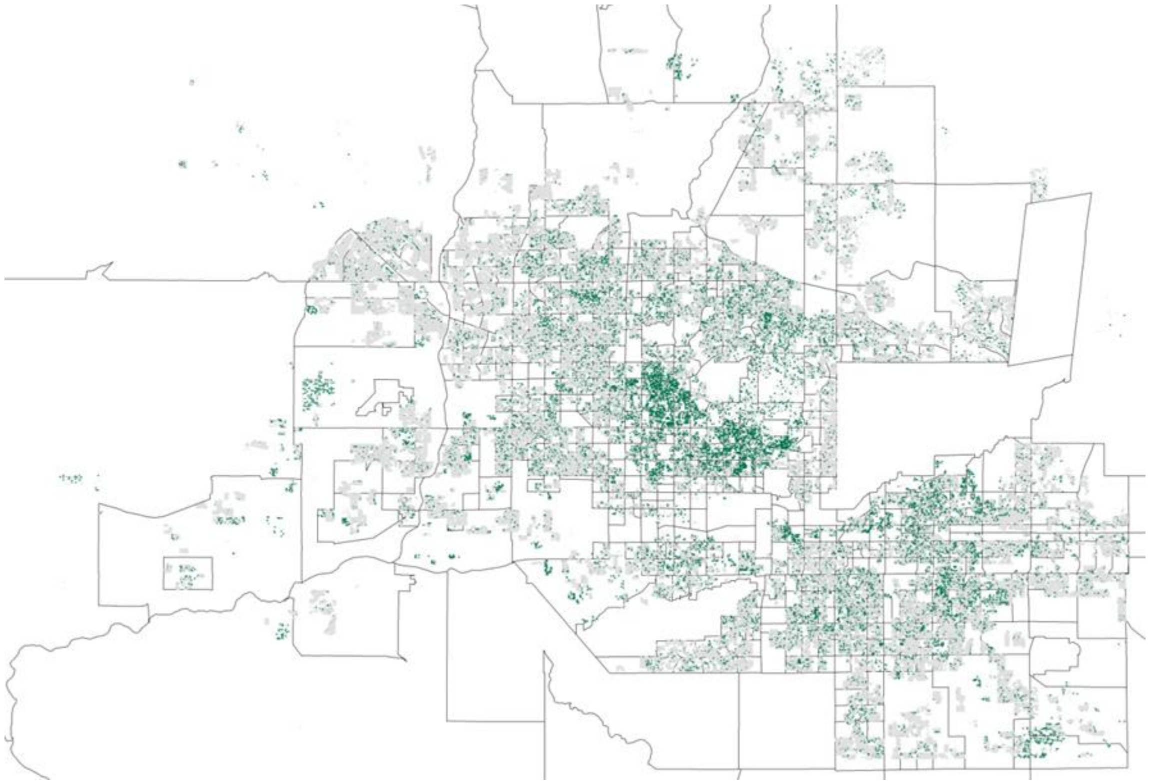

Figure 2. Housing transactions with a green landscape classification

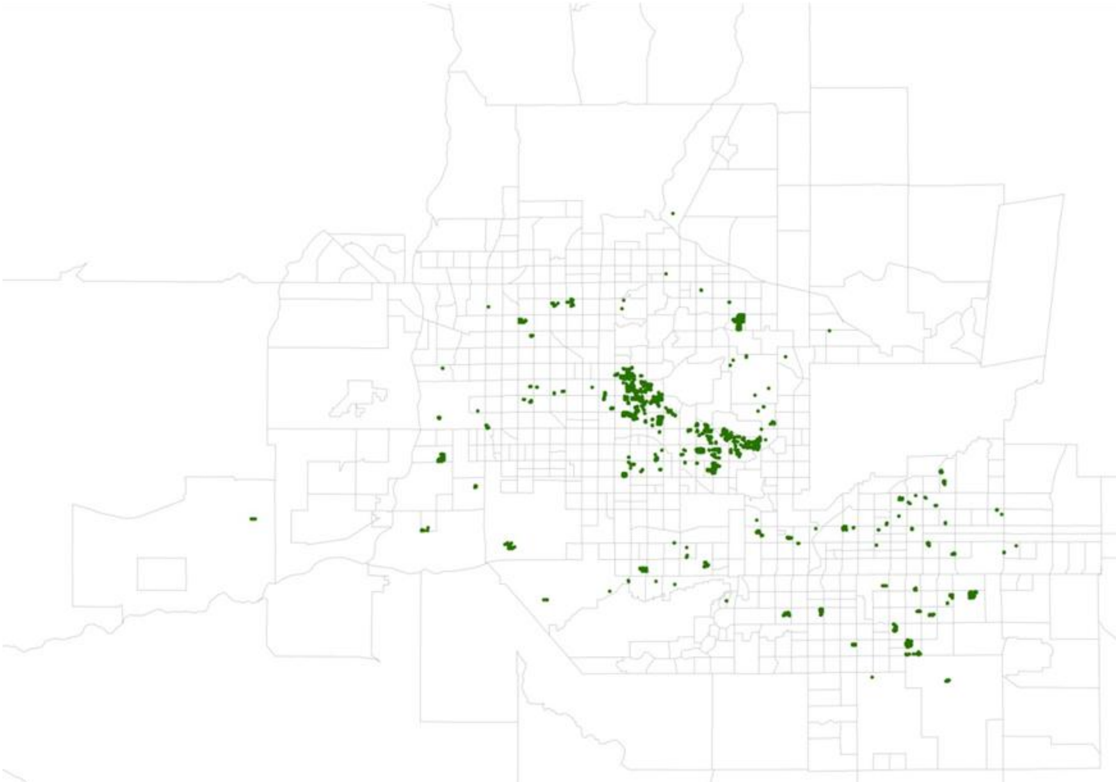

Figure 3. Subdivisions classified as “green”

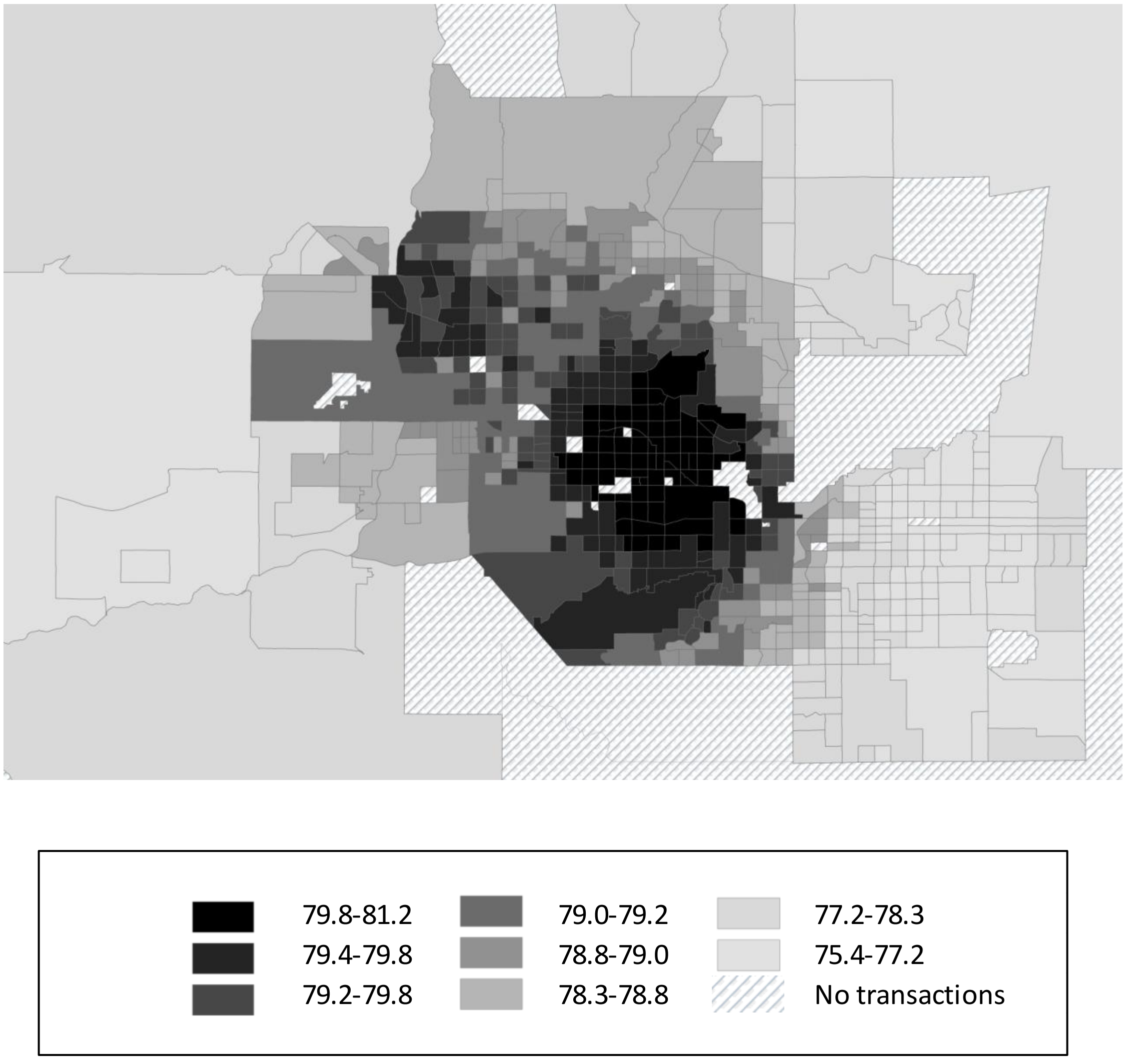

Figure 4. Spatial variation for July 2005 PRISM minimum temperatures.