# QUANTITATIVE RESTRICTIONS AND RESIDENTIAL WATER DEMAND:

## A SPATIAL ANALYSIS OF NEIGHBORHOOD EFFECTS

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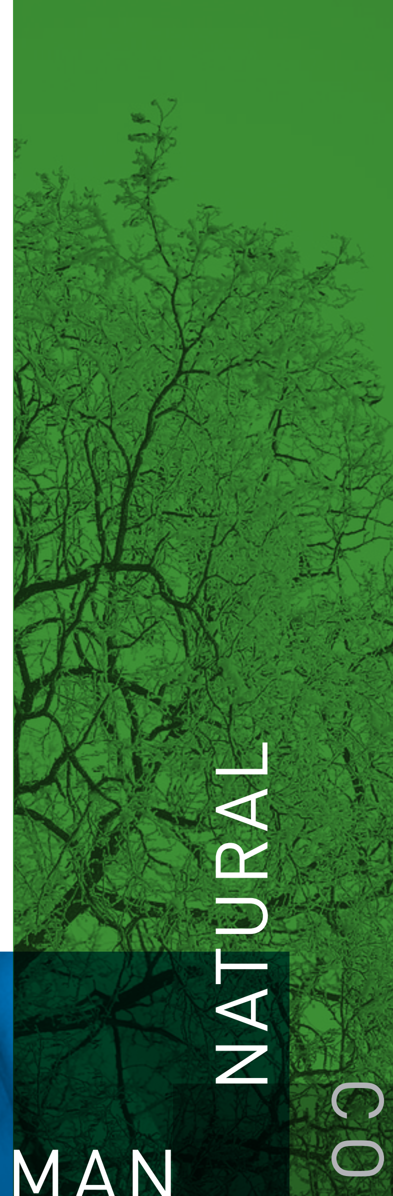



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# Quantitative Restrictions and Residential Water Demand: A Spatial Analysis of Neighborhood Effects

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**Abstract:** This article investigates the role of spatial pattern in residential outdoor water use and implications for the efficacy of non-price restrictions. Drawing on a spatially explicit dataset, the analysis characterizes latent neighborhood effects in households' outdoor water use and how these effects vary during water restrictions. Results illustrate that spatial patterns in water use vary across time periods and parcel sizes, and that correlations during water restrictions differ from those during other periods. Water use patterns of this type, largely overlooked by the current literature, have direct implications for the effectiveness of monitoring strategies used to promote compliance with non-price restrictions.

**Keywords:** water demand, lawn, neighborhood, water management, watering restrictions, spatial autocorrelation

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## I. Introduction

Among the defining characteristics of suburban residential water demand is a high proportion of overall consumption from outdoor uses such as lawn irrigation and pools, resulting in part from a relatively high ratio of lawn to lot size [Robbins and Birkenholtz, 2003]. Outdoor uses constitute an average of 50 to 70 percent of all household water use nationally [AWWA, 2009]. As peak demand for these outdoor uses tends to occur during lower-rainfall summer months, this tends to exacerbate water shortages during peak demand season[1].

Municipalities facing excess demand for water, especially during summers, have experimented with various demand side management policies to reduce household water use. These policies can be classified into price and non-price policies. Non-price policies include restrictions and bans on the quantity and timing of outdoor usages during peak demand seasons, audits to detect leaks, and incentives to install low-flow equipment. Price policies include increasing the frequency of billing, seasonal pricing (charging a higher price during summer when outdoor demand is the highest), and more recently, increasing block tariffs (charging higher prices each time consumption crosses predetermined quantity thresholds) [Olmstead et al., 2007; Renwick and Archibald, 1998)].

Of these two policy types, the economics literature gives much greater emphasis to price policies. Despite an extensive literature[2] addressing water demand patterns and elasticity [e.g., Hanemann, 1998; Espey et al., 1997; Dalhuisen et al, 2003], there is less attention to the ways in which non-price factors interact with water pricing to influence outdoor water consumption. For example, studies estimating price elasticity generally incorporate non-price policies, if at all, as binary variables. There has also been less focus on the influence of household, landscape and other variables on the efficacy of non-price policies, including systematic influences of spatial and landscape patterns. [3] As a result, the economics literature provides limited insight into some of the primary tools used by municipalities to manage outdoor water use.

One of the primary challenges with residential non-price water conservation measures is compliance[4]. More specifically, the expense, difficulty and political unpopularity of monitoring constrains the capacity of cities and towns to police outdoor water use and hence encourage compliance. Compounding this difficulty, municipalities typically lack information to help target

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[1] Massachusetts Municipal Association, http://www.mma.org/public-works-energy-a-utilities/2793-summer-raises-water-use-concerns, last access, May 10th, 2010.

[2] This includes contributions estimating the influence of water price on demand, with a common emphasis on the effects of pricing structure (e.g., Renwick and Archibald, 1998; Renwick and Green, 2000; Timmins, 2003; Olmstead et al., 2007).

[3] An exception is the effect of weather. Significant effort has gone into modeling weather and price effects so that an accurate estimate of their influence on water demand is captured (e.g., Renwick and Archibald,1998; Renwick and Green, 2000; Timmins, 2003; Olmstead et al., 2007).

[4] Personal communication, Mr.Tim Henry, Director of Water Utility, Town of Ipswich, MA. For similar scenarios in other parts of the country. Texas: http://www.msnbc.msn.com/id/32145286/ns/weather/, California: http://www.leakbird.com/water-conservation/sprinkler-tickets-15-water-police-officers-now-prowl-los-angeles-neighborhoods-for-water-infractions-associatedpress, last access date: May 25th, 2010.

monitoring activities towards households most likely to violate restrictions, instead relying on *ad hoc* mechanisms such as neighbor reporting[5]. Resulting monitoring efficacy and patterns of outdoor water use are unlikely to be optimal. For example, reliance on neighbor reporting to target monitoring and enforcement activities will be inefficient if certain neighborhoods as a whole violate restrictions (i.e., if neighbors reinforce each other's violating behavior, leading to spatial correlation in compliance). Such patterns are more likely when high water consuming households tend to occur in clusters, all else held equal.

Outside of the economics literature it is established that household landscaping activities are often influenced by latent spatial correlation—or neighborhood effects—leading to a dependency of household decisions (e.g., to water lawns) to those of neighbors. These spatial effects are often overlooked in the economics literature, promoting a perhaps misleading conclusion of spatial homogeneity in household responses to price and non-price policies, including reactions to non-price restrictions. Given that that compliance with non-price policies may be spatially dependent and correlated, development of effective residential water management requires insight on both average policy effects, as well as how these effects vary across landscapes.

Drawing on a unique, spatially explicit panel dataset from the town of Ipswich, Massachusetts, this article characterizes latent spatial patterns—or neighborhood effects—in households' outdoor water use and how these effects vary during periods of water use restrictions. The objective is to better understand the impact of non-price strategies, specifically quantitative restrictions, in managing residential outdoor water demand across residential landscapes. Developed models are grounded in the hypothesis that observed neighborhood correlations in landscaping behavior may be associated with similar relationships in outdoor water use. Such relationships can help identify spatial patterns in behavior during water restrictions directly applicable to household compliance and monitoring. Thus far, the literature gives minimal attention to such possibilities, overlooking information that could lead to the design of more effective policies for demand-side water management.

Model findings provide insight on the potential efficacy of non-price demand management tools when responses vary over the residential landscape. The model also provides information allowing better prediction of areas and parcel types with particularly high and/or low rates of outdoor water use during times of restrictions, after accounting for price, weather and other household attributes typically included in household water demand models [Renwick and Archibald, 1998; Renwick and Green, 2000; Timmins, 2003; Olmstead et al., 2007]. Water use patterns of this type can have direct implications for the effectiveness and spatial targeting of monitoring used to promote compliance with non-price restrictions.

## II. Neighborhood Effects and the Efficacy of Non-Price Policies

5 Drought Turning Texas Dry As Toast: Water Restrictions leads to extreme conservation efforts, Associated Press, 7/25/2009 http://www.msnbc.msn.com/id/32145286/ns/weather, last access date: Feb, 17th, 2011. Water Restrictions Imposed, GateHouse News Service, 09/05/2007. http://www.wickedlocal.com/ipswich/town_info/x822999167, Last Access date: Feb, 17th, 2011.

Utilities often combine price and non-price measures to promote conservation during periods of peak demand. Non-price conservation programs can be either voluntary or mandatory, and may include public information campaigns, installation of low-flow appliances, rationing, outdoor watering restrictions or bans, and increased billing frequency.[6] These can be classified into three broad categories: informational strategies, technological change and quantitative restrictions. Informational strategies and technological changes aim to promote long-term demand reduction. Quantitative, non-price restrictions are short-run tools to reduce water use during periods of peak demand [Glennon 2009].

Among the primary studies assessing effectiveness of non-price measures are those of Renwick and Archibald [1998] and Renwick and Green [2000]. Based on household-level panel data from Santa Barbara and Goleta counties (CA) during the drought of 1985-92, Renwick and Archibald (1998) find that water allocation policy reduces demand by 28.2 percent (4.58 HCF). The ban on outdoor uses in the Santa Barbara County also decreased water use by 4.37 HCF or 16 percent. The follow up study [Renwick and Green 2000] draws data from eight water agencies in California, and finds that most non-price measures have a statistically significant effect on water demand. Restrictions caused the greatest reduction of 29% (3.3 HCF) followed by rationing at 19% (2.1 HCF). Timmins [2003] similarly finds non-price policies effective, albeit only in conjunction with price policies.

These and other studies, however, fail to address spatial patterns that may be instrumental for policymakers seeking to enhance policy effectiveness. For example, it is possible that policy effects might differ across neighborhoods and/or parcel types, with different rates of compliance, such that utilities might be able to increase policy efficacy by targeting policies or enforcement in particular areas. In some cases, these areas might not correspond to predetermined political boundaries, so that simple binary variables (e.g., identifying towns) will be unable to capture such patterns. In other cases, latent spatial patterns in water use might vary across parcel types (e.g., smaller or larger parcels) or time periods (e.g., when restrictions are or are not in place), further complicating analysis of water use restrictions.

Hypotheses regarding latent spatial patterns in household water use are not without foundation. In contrast to the economics literature which tends to downplay the relevance of spatial pattern, research in the non-economics literature identifies a variety of spatial factors that influence households' landscaping decisions and associated water use patterns [Bockstael 1996]. These include factors related to the influence of landscaping on property sales prices [Anderson and Cordell, 1985; Morales et al 1976]. Other less studied landscape preferences may also play a role, however. Among these are dimensions of household landscaping that cause spatial dependence in behavior across proximate parcels, leading to neighborhood patterns in outdoor water use.

Evidence of neighborhood patterns in landscaping decisions is well established [Richards et al. 1984, Jim 1993, and Routaboule et al. 1995]. These and other studies observe that

[6] Other measures include retrofitting and water audits.

neighborhoods tend to have similar plant species and landscape elements; they also find mimicry in landscape decisions and layout. Zmylsony and Gagnon [1998], for example, find that proximal front yards share more common characteristics than more distant yards. Residents in a given street section are influenced by the shape, color and location of the vegetation they see in the front yards of their nearest neighbors. It might be argued that the observed mimicry in vegetation and landscaping style could be due to persistence in culture, influence of weather and soil conditions affecting the available native species of vegetation and zoning regulation. Evidence of neighborhood effects in other areas of consumption, however, suggests that these effects may persist even once one controls for such factors. For example, similar patterns have been found in residential energy consumption—a finding used by utilities in efforts to encourage more energy efficient behavior among neighbors [Iyer et al. 2006].

Lot sizes can also play an important role in the outdoor water demand [Renwick and Archibald, 1998; Olmstead et al., 2007]. Community zoning patterns promote clustering of similar size lots (e.g., large lots tend to neighbor other large lots), so that observed spatial pattern in landscaping and associated water use might reflect commonalities in landscape preferences related to parcel size. Moreover, households in certain lot sizes might be more or less likely to mimic neighbors' watering behavior. For example, households on larger, more expensive "showcase" lots might have a greater incentive to maintain landscaping that corresponds to neighborhood norms, given potential impacts on property values. As a result, efficient use and targeting of non-price policy may require information not only on spatial pattern in compliance but also on the potential related influence of lot size and other parcel characteristics.

## III. Data and Application

To evaluate such patterns in a case study location, we develop a spatially explicit model of water demand for the Town of Ispwich, MA. This town lies 24 miles north of Boston, MA in Essex county, and is part of the Boston Metropolitan Statistical Area. Water policy and scarcity is particularly relevant in this community. The Ipswich River – the source for 50% of the Town's water supply – was named one of the ten most threatened rivers in the country by American Rivers in 2003. The river often experiences low-flow and no-flow conditions during summers when water demand is at its peak. Hence, water policy- and the efficacy of non-price water restrictions – are considered issues of paramount importance [Polsky et al.2009].

The Town uses non-price policies of reduce residential water demand in the form of outdoor watering restrictions and bans. The combined reservoir storage capacity for the Town of Ipswich is 91.4 million gallons. When the water storage level falls below 46 million gallons, outdoor water use restrictions are triggered. When levels fall to 45 million gallons, a ban comes into effect. Bans are a more stringent gradation of the restrictions. The difference between restrictions and bans is the particular constraints imposed on the outdoor usage. Under restrictions, lawn watering is permitted, but constrained to handheld hosing between 9pm and 5am. Moreover, pools cannot be filled with public water. Cars can be washed with a pail, but cannot be hosed down. Under bans, there can be no outdoor water use.

To assess the potential impact of these two types of restrictions in Ipswich, a unique, geo-referenced panel dataset was compiled using data from multiple sources, with water usage for each household obtained from metered data from the town's water utility. Variables, data sources, and summary statistics are provided in Table 1. The primary dataset covers 1900 single family households from July to December 2002, with an ancillary dataset of water usage only for the same households from September to October 2003.

The time period of focus in this paper is the period of quantitative restrictions in 2002, between September and October. This period is chosen for study necessary data, including data on property attributes, are available only for 2002. In order to observe if the watering behavior and latent neighborhood effect during this period of watering restrictions is different from other months of the year, we test equivalent number of months immediately prior to restrictions of 2002 (July and August) and an equivalent period after (November and December). Since any change in watering behavior could be influenced by the season, when also test the same period as when restrictions were in effect the following year, September and October of 2003. Because data on property characteristics are only available for 2002, the analysis requires an assumption that these characteristics do not change between 2002 and 2003. This assumption is likely a reasonable approximation for the short time period in question, but would become increasingly questionable for any analysis over longer time periods. Watering behavior during the four periods is compared, each period covering two months.

Other data used to estimate the water demand model can be grouped into four categories: water prices, household characteristics, property characteristics and weather. In addition to water tariff, households in the Town of Ipswich are charged sewer rates which are calculated based on metered water usage. As a deliberate measure to curtail development, the town has restricted the sewer infrastructure to the area surrounding the town center. As a result, about half the town population is connected to the sewer and the reminder relies on septic disposal. The implication of this policy is that customers connected to the sewer face a different tariff structure for water (which combines water and sewer rates), while those unconnected to the sewer face only the water tariff. Accordingly, our data allow for systematically varying slopes between connected and unconnected properties, allowing the effects of price changes to be modeled for connected households.

Only household characteristic for which data is available is the size of the household. We obtain this data from the Town census, latest of which is from 1998. Additional data were collected to characterize the property or parcel characteristics from the town. Since we are concerned with outdoor watering, we collected data on lawn size and slope of the parcel (because of run-offs). Lawn size for each property was estimated using GIS layer maps created by the Town in 2002 and slope information was calculated using GIS data obtained from the United States Department of Agriculture. To control for factors influencing indoor water uses, we incorporate data on number of rooms and bathrooms, from the Town's property assessment data for the year of 2002.

Previous studies in the literature have found that weather can play an important role too in outdoor water demand [Howe and Linaweaver, 1967; Renwick and Archibald 1998; Renwick and Green 2000]. To account for these effects, the data also include information on weather patterns. The traditional approach to these effects in the economic literature is to include temperature and precipitation in the model. This simple approach, however, does not account for the complex interaction between temperature, precipitation, solar radiation, humidity and wind speed that determines evapotranspiration. Following methods used in the commercial landscaping business and advocated by American Society of Civil Engineers (Allen et al.2005), using data collected from National Oceanic and Atmospheric Administration (NOAA), National Climatic Data Center, and from local weather stations operated by lawn care businesses, the variable potential evapotranspiration (*ETO*) is calculated using the Penman-Monteith equation (ASCE, 2005). *ETO,* along with precipitation, is used to calculate a moisture index (M index) which varies from -1 (arid) to 1(saturated) [Feddema, 2005]. These and other model variables are summarized in Table 1.

## III. Empirical Model

We begin with a water demand specified following the prior specifications in the literature, modeling the natural log of quantity demanded as a function of price, property characteristics, household characteristics and weather variables. A random effects, trans-log model is used to estimate the demand function, where $\mu_i$ represents household specific error term and $\varepsilon_{it}$ is the remaining error [cf. Olmstead et al., 2007][7]. Unlike the conventional water demand model, our model allows for neighborhood to influence a household's water demand.

Since we do not know the exact manner in which neighbors influence each other's landscaping and thereby outdoor watering behavior it is not possible to incorporate a deterministic relation for the same in a conventional water demand model. This is an opportunity for future research. In this paper, the goal is more fundamental—we evaluate whether the conventional water demand model ignores the influence of neighborhood, by testing the residuals of this demand model for spatial patterns. If there are statistically significant spatial patterns remaining in the residuals (i.e., not captured by the model), it indicates that neighbors do influence outdoor watering behavior. To conduct this analysis, the empirical model tested here is a conventional random effect model that allows for spatial autocorrelation in errors.

The empirical model used in this paper draws from the theoretical model described in equation [1] below [Anselin 1988; Baltagi 2003].

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7 Traditionally empirical analyses of panel data also tests for the fit of fixed effect model. In our case, as mentioned in the data section, property characteristics and household size is only for the year of 2002, hence does not vary across the studied months. This renders the estimation of a fixed effects model to capture their coefficient impossible, without unrealistic assumptions. In the fixed-effect approach, the space specific aspects needs to be specified with dummy variables, given that there are 1900 households, it would lead to degrees of freedom issues given the size of the sample, available for analysis. In random effects approach, the space specific effects are assumed to be random.

$$y_{it} = \alpha + X_{it}^{'}\beta + \varepsilon_{it} \qquad [1]$$

The variables are organized by spatial units *i (i=1…N)* and time periods *t (t=1…T)*. Here $y_{it}$ is the observation on the *i* th region for the *t* th time period, $\alpha$ is a scalar term, $X_{it}^{'}$ denotes *k x 1* vector of observations on the regressors, $\beta$ is the *k x 1* vector of slope parameters and $\varepsilon_{it}$ is the regression disturbance. The error term is assumed to incorporate unobserved neighborhood effects, household specific random element and the usual random error. The overall error term $(\varepsilon_{it})$ in [1] consists of two components: household specific random element$(\mu_i)$ and the error term$(\phi_{it})$. The error term $(\phi_{it})$ contains a spatially autoregressive term and the usual random error that is assumed to be *IID* $(0, \sigma_v^2)$. This is described by equations [1a and 1b] in the vector form assumed to have random region effects and spatially autoregressive reminder disturbances.

$$\varepsilon_t = \mu + \phi_t \qquad [1a]$$
$$\phi_t = \lambda W_N \phi_t + \nu_t \qquad [1b]$$

We assume that $\mu$ and $\nu$ are independent. $\lambda$ is the scalar spatial autoregressive coefficient with $|\lambda| < 1$. $W_N$is an *N x N* weighting matrix with zeros across the diagonal and $\nu$ is the random error term that satisfies the classical assumptions of *IID*, with constant variance. The empirical model in equation [2] expands [1,1a and 1b] specifically identifying the categories of variables included in the estimated model. The model described in equation [2] is estimated for each of the four periods described in the previous section.

$$y_{it} = \alpha + \delta p_{it} + \gamma z_i + \beta x_i + \varphi m_t + \mu_i + \lambda W_N \phi_t + \nu_{it} \qquad [2]$$

Where

$y_{it}$ = Natural logarithm of metered water usage,
$p_{it}$ = Natural logarithm of water prices
$z_i$ = Vector of property characteristics
$x_i$ = Vector of household characteristics
$m_t$ = Vector of weather variables
$\mu_i$ = Household specific random element
$W_N \phi_t$ = Spatially autoregressive disturbance
$\nu_{it}$ = Random error term $\nu_{it} \sim N(0, \sigma_v^2)$

In the context of outdoor watering behavior, which is a highly visible activity, households are likely to observe not only their immediate neighbor's landscaping, but also their watering behavior. This may lead to mimicry which manifests as a correlation among the behavior of proximate parcels. The quantitative measure of the effect of immediate neighbors of water usage is described as neighborhood effect; these effects may extend both to water use and also to associated influences of water use restrictions.

In order to test for these neighborhood effects, estimated residuals ( $\varepsilon_{it}$ ) for each of the time periods are tested for spatial autocorrelation using Moran's I statistic [Anselin, 1988]. This statistic compares the value of a variable at any one location with the value at all other locations, and measures the extent to which the occurrence of an event in an aerial unit constrains, or makes more probable, the occurrence of an event in a neighboring areal unit. Here, immediate neighbors are defined as property adjacent to a given property. Similar to correlation coefficient, it varies between –1.0 and + 1.0[8]. Statistically significant spatial autocorrelation indicates the presence of a neighborhood effect not otherwise captured by model variables [Anselin, 1988]. The presence, location and type of these effects provides insight into spatial dimensions of water use, including compliance with water use restrictions. That is, we assess whether there are systematic components of water usage that are unexplained by the model and correlated over space.

## V. Model Results

Results of the regression analysis are presented in Table 2. Model variables are jointly significant at p<0.01. $R^2$ values range from 0.09 to 0.14—a similar range to those found in prior analyses of water demand [Renwick and Archibald, 1998; Olmstead et al., 2007; Olmstead and Mansur, 2010]. As shown by model results (i.e., the coefficients on *pool* and *lawn*), most of the total usage is associated with outdoor uses.

Although the primary emphasis of the analysis is on spatial neighborhood effects and implications for the efficacy of non-price policies, we begin with a brief overview of model results. As expected, a number of variables with substantial cross-sectional variation (e.g., household size, number of bathrooms and pool ownership) have a statistically significant influence on water demand. Influence of weather captured by the moisture index (*m_index*) is statistically significant during and immediately before periods of outdoor watering restrictions and bans. A single unit increase in moisture index, implying more rainfall or moisture in the soil, decreases water demand by 17 percent during the period of restrictions and ban. Compared to other periods, magnitude is the highest during the restrictions period.

Several variables capture property and household characteristics in the estimated model (table 1). These include seven variables characterizing lawn size (*lawn* and *lawn_sq*), slope of the property (*steep, flat*), pool ownership (*pool ownership*), the number of bathrooms (*bathrooms*) and household size (*householdsize*). In order to test whether the influences of these characteristics differ between properties that are connected and unconnected to the town sewer, each these variables are interacted with a binary variable for being connected; interacted variables appear with (*_c*) appended.

As expected, lawn size affects water usage; during restrictions and bans a single acre increase in lawn increases usage by 19.5 percent. The marginal effect of increase in lawn size is

[8] $I = \dfrac{N\sum_i \sum_j W_{i,j}(X_i - \bar{X})(X_j - \bar{X})}{(\sum_i \sum_j W_{i,j})\sum_i (X_i - \bar{X})^2}$, where $N$ is the number of cases, Xi is the variable value at a particular location, Xj is the variable value at another location, X is the mean of the variable, and Wij is a weight applied to the comparison between location *i* and location *j*.

relatively smaller during quantitative restrictions, compared to the period prior to restrictions (24 percent). This indicates that during restrictions households reduce their irrigation; the marginal effect of lawn size on water usage is reduced by 4.5 percent. Usage attributable to additional bathrooms is generally higher during summer than winter, which is not unexpected. However, there is a small decrease in the marginal contribution of each bathroom during quantitative restrictions. The presence of a pool adds between 17 and 31 percent to a household's usage. Interestingly, this marginal increase is greatest during periods of water restrictions, implying that restrictions may have relatively little impact on households' use of water to fill pools. Results show no statistically significant difference in the influence of household and property characteristics between connected and unconnected households (i.e., interaction variables are not statistically significant).

The price of water is included in the model using the variable *lncp_connected*. Though this variable has received extensive attention in the literature, it plays only a minor role the current context, and is not a focus of the analysis. Among the reasons for this lack of emphasis is our focus on non-price restrictions, together with lack of price variation observed during each of the modeled periods. As a result, the estimated coefficient in this case offers little insight into households' long-term price responsiveness. It is primarily included as a control to enable accurate estimation of the influence of other, non-price variables.

Drawing from these results, the point of departure for the analysis of latent neighborhood effects is the observation that non-price water use restrictions in Ipswich caused limited reduction in overall water use. Indeed, holding price and other factors constant, predicted household water use is greater during time periods in which quantitative restrictions were in place, compared to other modeled periods. For example, drawing from the estimated coefficients of models [1] through [4], a household with mean characteristics is predicted to use 1018 cubic feet during restrictions, compared to 933 cubic feet during months prior to restrictions and 796 cubic feet during the corresponding period of the following year. What is unclear from these broad estimates is whether this lack of responsiveness, or high water use during restrictions, is homogeneous across parcels or spatially clustered in neighborhoods. If the latter, results may help identify potential areas in which increased monitoring activities might be effective at promoting compliance.

## VI. Neighborhood Effect on Water Demand

To quantify neighborhood effects in each of the four time periods, residuals from the four models in table 2 are merged with the assessment parcel map of the town from 2002, using geographical identifiers for each observation. The estimated Moran's I spatial autocorrelation statistics and associated graphs associated are presented in table 3. These statistics can be presented graphically as a scatter plot with the spatial lag of the residuals on the vertical axis and original residuals in the horizontal axis. Results are standardized so that units in the graph correspond to standard deviations.

There are four types of spatial autocorrelation representing different types of neighborhood effects. As noted above, these are represented graphically by the location of the spatial lag of the residuals. These include *high-high* (upper right) and *low-low* (lower left) for positive spatial autocorrelation, and *high-low* (lower right) and *low-high* (upper left) for negative autocorrelation. The two most relevant categories are high-high, which capture clusters of high water use households or neighborhoods, and low-low, which capture low water use clusters of households or neighborhoods. If there is no spatial autocorrelation there will be no discernable pattern the graph with most of the data points surrounding the origin. The slope of the regression line is defined as the Moran's I statistic. To test the neighborhood effect, a first-order queen contiguity matrix, i.e., any move a queen could make in a chess board, is used to define neighboring parcels [Anselin, 1988]. This means that immediate adjacent parcels at all sides to a given parcel are defined as the parcel's immediate neighborhood for purposes of establishing spatial patterns. Statistical inference (i.e., hypothesis testing) for Moran's I is based on a permutation approach, in which a reference distribution is calculated for spatially random layouts for the same data [Anselin, 1988].

In order to assess the potential role of parcel size in estimated neighborhood effects, the distribution of the lot sizes in the Town of Ipswich, MA is used to demarcate the properties into size categories. The distribution of the lot sizes is shown in Figure 2. Lot size distribution in Ipswich is bi-modal with a median of 0.80 acres, with a small number of outlier parcels between 2.24 and 5 acres. Based on this distribution, we characterize parcels of less than 0.80 acres as "small," parcels over 0.80 as "large," and parcels over 2.24 acres as "very large." Analysis of neighborhood effects is conducted both for the full sample (i.e., all parcels regardless of size), as well as for parcels within each size category.

Results are presented in table 3.[9] Interestingly, full sample results find no evidence of statistically significant neighborhood effect during the period of water use restrictions [September 2002 through October 2002], although these effects are found for the corresponding (no restriction) period the following year, as well as during the two month period in 2002 just prior to the imposition of restrictions. This suggests the general presence of neighborhood correlations in outdoor water use that disappear when restrictions are imposed. One possible explanation is that households may make particular efforts to *not* imitate the watering behavior of their neighbors when restrictions are in place; that is, the presence of restrictions causes behavioral changes which dominate neighborhood correlations which might otherwise occur.

Additional insight is gained by considering neighborhood effects according to parcel size. Among smaller parcels (<0.80 acres), neighborhood effect is only statistically significant ($p<0.10$) during the winter period (i.e., the period with minimal outdoor use). This is an unexpected result, as winter uses are not generally driven by visible outdoor consumption (e.g., landscaping, lawns and pools). Among larger parcels (>0.80 acres), in contrast, statistically significant correlations are found both in winter and in the time period immediately preceding the imposition of water use restrictions. Again, however, no statistically significant neighborhood effects are found during the period of water restrictions. Results differ, however,

[9] Graphical results are suppressed for conciseness, and are available upon request.

among very large parcels (>2.24 acres). For these parcels, all periods have a statistically significant neighborhood effect, with magnitudes ranging from 3.2% to 4.8%.

This significant change in the influence of neighbors among different groups of parcel sizes is depicted in Figure 3 (top row), which shows Moran's I graphs for each of the parcel size categories during periods of water restrictions. The final panel shows results for very large parcels (>2.24 acres), with two distinct clusters in the top right (high-high) and lower left (low-low) quadrants. These results demonstrate that among households in parcels over 2.24 acres, there is strong mimicry in outdoor water use during quantitative restrictions, with some households mimicking neighbors' higher usage and others mimicking neighbors' lower usage. This correlation is absent in smaller parcels during periods of water restrictions.

Similar patterns are found during the parallel time period in 2003 when no water use restrictions were in place. Figure 3 (bottom row) shows parallel Moran's I graphs for this period. Again, we find no statistically significant mimicry in behavior for smaller (<0.80 acres) and larger (>0.80 acres) parcels, but strong positive correlation for very large parcels (>2.24 acres). In this case, however, the strength of the spatial autocorrelation for very large parcels is sufficient to cause a statistically significant effect for the full sample.

These findings suggest a strong neighborhood effect in water use among very large parcels that applies regardless of the presence of water use restrictions. Of particular note are households in the high-high category, implying clusters of neighbors with systematically higher than average water usage, *ceteris paribus*. Within these neighborhoods, common reliance on neighbor reporting to identify violators of water restrictions is unlikely to be effective, as violating households are likely to occur in "violating clusters." That is, households adjacent to violators (or high water users) are more likely to be violators or high users themselves, and would presumably be less likely to report their neighbors' activities. Conversely, those very large parcels using less water are likely to neighbor other households with similar behaviors, and would hence be less likely to observe violations which could be reported. Although results suggest that neighbor reporting may be less effective within clusters of very large parcels, these areas are also likely to represent areas in which targeted monitoring for violations may be particularly cost-effective, as monitoring in small geographical areas may reveal large numbers of clustered violators.

In addition to implications for compliance during periods of water restrictions, results provide insight relevant to longer-term programs to reduce water use. Among small parcels, for example, we find little evidence that households mimic neighbors water use behavior. Hence, among these parcels, results suggest that educational and other non-regulatory efforts to reduce water use are likely to be most effective when targeted to *all* households—a more costly strategy. In contrast, for very large parcels, policymakers might seek to target a smaller number of households with more intensive programs (e.g., in person meetings to discuss water saving strategies), relying instead on household mimicry to transfer approaches to neighboring households. Such approaches are likely to be most viable in areas where neighborhood effects are strong, as identified by models such as those illustrated here. The finding of *low-low* clusters in large parcels that is large parcel neighborhoods mimicking each other into lower water consumption was unexpected. Future research studying the reasons behind the *low-low* clusters can be very beneficially in formulating policies for similar large size parcel owners who mimic neighbors into consuming more.

Taken together, information on spatial water use patterns (figure 1), estimated demand models (table 2), and estimated spatial correlations (table 3; figure 3) provide a more comprehensive perspective on community water use and reactions to use restrictions than that available through traditionally estimated demand models alone. For example, unlike traditional demand models viewed in isolation, results here could be used to identify specific areas and parcels in Ipswich whose shared behavior leads to excessive neighborhood water use compared to otherwise identical parcels elsewhere. Results such as these can help inform local implementation and enforcement of non-price water restrictions, leading to more cost-effective policy than would otherwise be possible.

## VII. Conclusion

This paper characterizes spatial effects on households' outdoor watering use and how these effects vary during periods of watering restrictions. Results demonstrate the types of insights which can be provided by models that emphasize households' reactions to non-price policies commonly used by municipalities to reduce water use, particularly when these reactions vary over space and across households. Of particular emphasis here are implications for efficacy, monitoring and compliance of water use restrictions. The focus of the analysis stands in contrast to the bulk of the economic literature on household water demand, which de-emphasizes the role of non-price policies in favor of greater attention to price responsiveness.

Model results illustrate that spatial correlations in water use vary across time periods and parcel sizes, and that neighborhood effects during times of water restrictions differ from those during other time periods. Revealed water use patterns suggest particular monitoring strategies that are likely to be more (or less) effective in promoting compliance within particular parcel clusters. For example, spatial autocorrelations identified for very large parcels suggest the potential cost-effectiveness of compliance monitoring targeted in these areas, and the likely inefficacy of neighbor reporting. Similar findings, however, do not apply to smaller parcels.

Although models illustrated in this paper illustrate some of the additional insights which can be provided by models addressing explicit spatial pattern in household water use, many questions remain for future work. The broader applicability of our specific findings outside of the case study area, for example, is unknown. Similar analyses in other municipalities and areas will be necessary to identify whether similar patterns apply elsewhere, or whether neighborhood effects and similar patterns in responsiveness to non-price water restrictions are largely idiosyncratic across communities. Moreover, while results here are able to identify clusters of high water using parcels—suggesting areas in which violations of water use restrictions are likely—they are unable to identify specific parcels that are in violation of these restrictions. Additional data and analysis, unavailable here, would be required to isolate similar patterns in the binary choice to comply with particular water use restrictions. Findings and related questions such as these suggest that researchers may wish to give greater attention to the divergent effects of the various non-price policies that might be implemented to influence water use nationwide, how policy effectiveness varies across household types, and how insight into spatial patterns in efficacy can help promote more cost-effective implementation.

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**Table 1**
**Model Variables and Summary Statistics**

| | | | All Households | | Connected to Sewer | | Not Connected to Sewer | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Description** | **Data Source** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| *Lntotalconsumption* - Total Household Consumption (Dependent Variable) | Individual household's Meter readings measured in 100 cubic feet. Variable is in natural log terms. | Water Utility, Town of Ipswich, MA | 893 | 1787 | 889 | 1421 | 1051 | 1978 |
| *Eto* Potential Evapotranspiration | Penmann-Montieth Equation for potential evapotranspiration | Data from Local weather stations, NOAA and NCDC | 0.68 | 0.44 | 0.68 | 0.44 | 0.68 | 0.44 |
| *M_index* Moisture Index | Index of Feddema(2005) | Data from Local weather stations, NOAA and NCDC | -1.00 | 0.52 | -1.00 | 0.52 | -1.00 | 0.52 |
| Property slope: *Flat* (0-3% gradient) | Binary variable, taking value of 1 if the gradient is between 0-3%, 0 otherwise | GIS layers from United States Department of Agriculture | 0.45 | 0.49 | 0.53 | 0.49 | 0.40 | 0.49 |
| Property slope: *Steep* (15-25% gradient) | Binary variable, taking value of 1 if the gradient is between 15-25%, 0 otherwise | | 0.28 | 0.45 | 0.36 | 0.48 | 0.219 | 0.413 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Lot size | in acres | GIS data, Assessor Office,Town of Ipswich, MA | 1.66 | 14.51 | 0.38 | 0.60 | 2.51 | 0.88 |
| *Lawn*<br>Lawn Size | in acres | Town of Ipswich, MA | 0.86 | 8.95 | 0.20 | 0.25 | 1.30 | 11.50 |
| *Householdsize*<br>Size of the household | in persons per parcel | | 3.01 | 1.46 | 3.02 | 1.69 | 3.00 | 1.29 |
| *Bathrooms*<br>Number of bathrooms | per parcel | Assessment Data from 2002,Town of Ipswich, MA | 1.47 | 0.52 | 1.43 | 0.51 | 1.57 | 0.51 |
| Number of Rooms | per parcel | | 6.41 | 1.85 | 7.00 | 1.90 | 6.09 | 1.39 |
| *Poolownership*<br>Pool | per parcel | | 0.09 | 0.29 | 0.07 | 0.26 | 0.093 | 0.29 |
| *Lncp*<br>Price | Per 100 cu.ft | Water Utility, of the Town of Ipswich, MA | 0.894 | 0.99 | N/A | N/A | 0.894 | 0.99 |

**Table 2**
**Estimated Water Demand Models**

| | [1] During Quantitative Restriction: September,2002 to October, 2002 | [2] Immediately Before Restriction: July, 2002 to August, 2002 | [3] Corresponding Time period In Following Year: September,2003 to October, 2003 | [4] Winter: November, 2002 to December, 2002 |
|---|---|---|---|---|
| *m_index* | -1.897*** | -1.179** | -0.341 | 0.124 |
| | (-5.68) | (-3.16) | (-1.85) | (1.29) |
| *steep* | 0.285 | 0.669 | 0.0717 | 0.0847 |
| | (0.74) | (1.48) | (0.34) | (1.73) |
| *flat* | -0.00237 | 0.152 | 0.0556 | 0.0123 |
| | (-0.01) | (0.34) | (0.28) | (0.26) |
| *steep_mindex* | 0.308 | 0.769 | -0.0871 | -0.131 |
| | (0.61) | (1.42) | (-0.31) | (-0.91) |
| *flat_mindex* | -0.0194 | 0.231 | -0.0150 | -0.210 |
| | (-0.04) | (0.43) | (-0.06) | (-1.55) |
| *lawn* | 0.195* | 0.240* | 0.0424 | 0.244** |
| | (2.00) | (2.41) | (0.51) | (2.90) |
| *lawn_sq* | -0.0287 | -0.0535* | 0.00641 | -0.0397 |
| | (-1.19) | (-2.14) | (0.32) | (-1.87) |
| *lawn_c* | -0.0849 | -0.416 | -0.444 | -0.677** |
| | (-0.29) | (-1.52) | (-1.79) | (-2.91) |
| *lawn_sq_c* | 0.0577 | 0.158 | 0.181 | 0.246* |
| | (0.38) | (1.15) | (1.41) | (2.10) |
| *householdsize* | 0.187*** | 0.229*** | 0.214*** | 0.266*** |
| | (8.67) | (10.39) | (11.79) | (14.33) |
| *householdsize_c* | 0.00358 | -0.0471 | -0.0441 | -0.0392 |
| | (0.12) | (-1.66) | (-1.80) | (-1.64) |

| | | | | |
|---|---|---|---|---|
| *bathrooms* | 0.183*** | 0.188*** | 0.270*** | 0.139** |
| | (3.49) | (3.47) | (6.14) | (3.07) |
| *bathrooms_c* | 0.0953 | 0.0838 | -0.0475 | 0.00840 |
| | (1.14) | (1.03) | (-0.67) | (0.12) |
| *poolownership* | 0.307*** | 0.170 | 0.232** | 0.254** |
| | (3.33) | (1.81) | (2.96) | (3.20) |
| *poolownership_c* | 0.181 | 0.245 | 0.227 | 0.0996 |
| | (1.17) | (1.61) | (1.74) | (0.77) |
| *lncp_connected* | -0.0709 | 0.0886 | 0.107* | 0.144* |
| | (-1.01) | (1.28) | (2.05) | (2.57) |
| *Intercept* | 3.890*** | 4.060*** | 4.843*** | 4.944*** |
| | (14.10) | (12.64) | (30.32) | (58.52) |
| F stat (p-value) | 0.00 | 0.00 | 0.00 | 0.00 |
| N | 3277 | 3859 | 3275 | 3915 |
| $R^2$ | 0.110 | 0.092 | 0.121 | 0.138 |

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01

**Table 3**
**Estimated Spatial Autocorrelations**

| Refer | Time Period | Moran's I | P-value |
|---|---|---|---|
| For All Parcels | Winter: Nov,2002 to Dec ,2003 | 0.0295 | 0.132 |
| | Jul, 2002 to Aug ,2002 | 0.0611 | 0.006 |
| | Sep, 2003 to Oct,2003 | 0.0857 | 0.001 |
| | Sep,2002 to Oct ,2002 | -0.0003 | 0.677 |
| For Parcels < 0.80 acres | Winter: Nov,2002 to Dec ,2003 | 0.0332 | 0.0970 |
| | Jul, 2002 to Aug ,2002 | 0.0165 | 0.2260 |
| | Sep, 2003 to Oct,2003 | 0.0291 | 0.1330 |
| | Sep,2002 to Oct ,2002 | 0.0112 | 0.3040 |
| For Parcels > 0.80 acres | Winter: Nov,2002 to Dec ,2003 | 0.0319 | 0.0980 |
| | Jul, 2002 to Aug ,2002 | 0.0398 | 0.0560 |
| | Sep, 2003 to Oct,2003 | 0.0195 | 0.1900 |
| | Sep,2002 to Oct ,2002 | 0.0045 | 0.3990 |
| For Parcels > 2.24 acres | Winter: Nov,2002 to Dec ,2003 | 0.0324 | 0.094 |
| | Jul, 2002 to Aug ,2002 | 0.0422 | 0.045 |
| | Sep, 2003 to Oct,2003 | 0.048 | 0.039 |
| | Sep,2002 to Oct ,2002 | 0.3981 | 0.001 |


**FIGURE 1**

**Average Daily Water Use in cu.ft., Parcels in the Town of Ipswich, MA (September & October, 2002)**

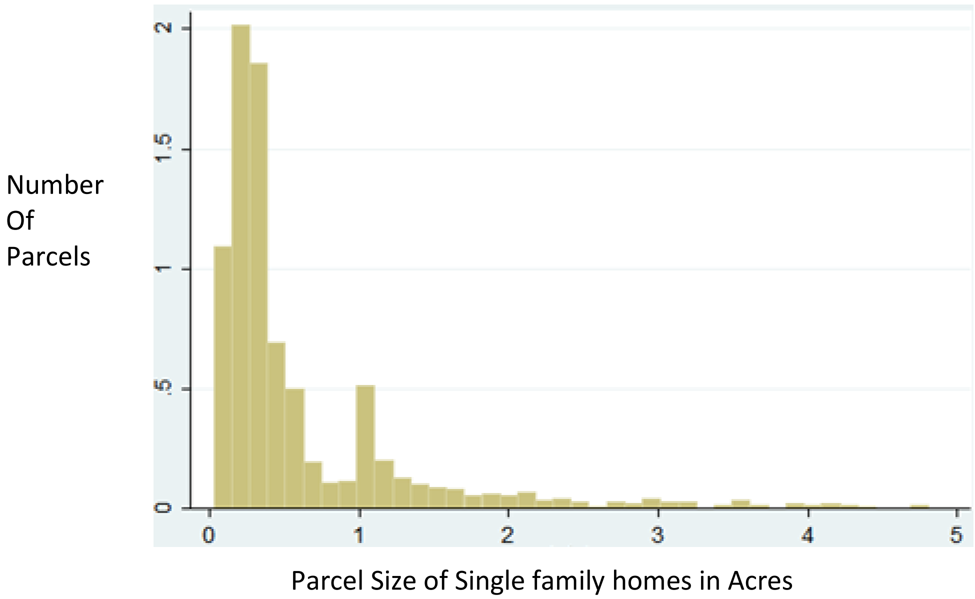


**FIGURE 2**

**Distribution of Lot Sizes, Town of Ipswich, MA (2002)**

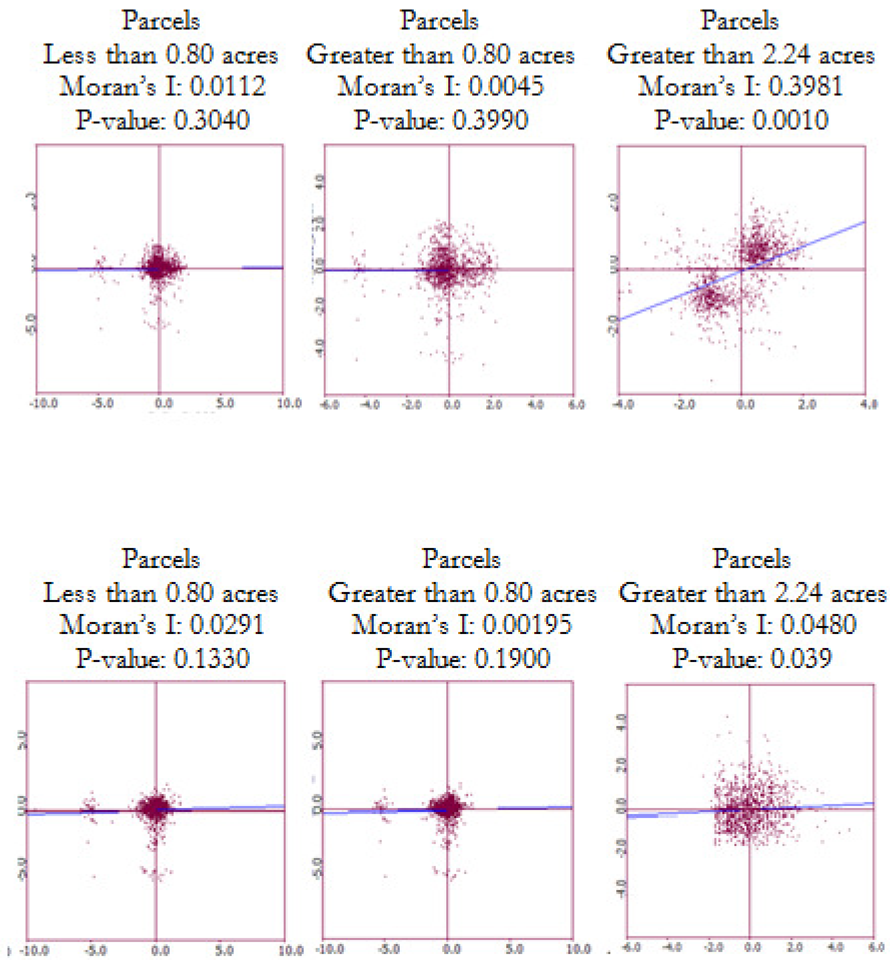


**FIGURE 3**

**Spatial Autocorrelation during Quantitative Restrictions (Top Row) and Corresponding Period in the Following Year (Bottom Row)**