Understanding Neighborhood Conforming Peer Effects on Household Lawncare Practices:

Implications for Nonpoint-Source Pollution Emissions

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Abstract

Reducing pollution levels in many water bodies requires control over household behaviors such as lawn fertilizer use linked to nonpoint source nutrient emissions. Informal neighborhood-scale conforming effects such as peer influences and cultural norms have been repeatedly theorized to affect many types of homeowner decisions. Yet these pressures have proven difficult to incorporate into rigorous economic models of residential lawncare decisions. This article integrates advances from the economics and lawncare literatures to develop a model of household fertilizer decisions that incorporates spatial conforming (or neighborhood) influences. Empirical implementation leverages geographic information system (GIS) parcel data to characterize conforming pressures using observable property characteristics for each sampled household relative to surrounding neighbors. We estimate conforming effects for two sequenced decisions—whether to fertilize, and if so with what frequency. Importantly, model implementation does *not* require that one directly observe the behavior of interest (fertilizer use) for all parcels in the study region—the standard approach used by economists to characterize spatial peer effects. The model is implemented using survey data from a sample of homeowners in the Baltimore metro region (in Maryland, USA), combined with spatially explicit parcel data for the entire region. Results demonstrate strong forces for spatial homogeneity over proximate parcels that can cause households to either increase or decrease fertilizer use relative to effects caused by individual household and parcel characteristics alone. These findings have direct implications for predicting household fertilizer use and nonpoint source emissions.

Keywords: fertilizer, residential lawns, spatial, conforming peer effects, nonpoint source pollution

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1. Introduction

Negative environmental impacts of residential grass lawns have led to growing attention to their management and motivations for different types of lawncare practices by households (e.g., Fuentes, 2021; Larson et al., 2016; Larson et al., 2020; Locke et al., 2019; Milesi et al., 2005). The literature on lawncare and landscape practices has grown dramatically in recent decades, leading to a general theoretical consensus that lawncare is a multi-scale process influenced by forces that manifest at the household, neighborhood, municipal, or larger spatial and functional scales (Chowdhury et al., 2011; Cook, Hall, & Larson, 2012; Polsky et al., 2014). Yet the strength of this theoretical consensus is not matched with similarly robust empirical evidence. With few exceptions, even studies that assert a role for multiple scales operating simultaneously in practice emphasize only one scale at a time. This disparity between theory and evidence reflects a long-standing social science tension between (1) traditional microeconomic perspectives (Johnston, Ndebele, & Newburn, 2022; Newburn & Alberini, 2016; Tran, McCann, & Shin, 2020; Zhou et al., 2009) that emphasize impacts of prices, household characteristics, parcel characteristics and governmental policies, and (2) non-economic, often more qualitative studies on collective perspectives (Larson & Brumand 2014; Sisser et al., 2016) emphasizing neighborhood- or municipal-scale effects for explaining lawncare behaviors.

Responding to this disparity, a small body of recent literature outside of the economics discipline has developed empirical models that rely on household survey data to characterize the influence of both household- and neighborhood-scale (conforming) covariates on households' fertilizer decisions (e.g., Carrico, Fraser, & Bazuin, 2013; Carrico et al., 2018; Fraser, Bazuin, & Hornberger, 2016; Fraser et al., 2013; Martini et al., 2015). This work often seeks to disentangle formal and informal neighborhood effects. For example, homeowners associations (HOAs) are formal neighborhood-scale institutions that can levy fees to encourage or require households to adopt specific lawncare behaviors. As such, households in HOAs are often found to have higher lawn fertilization rates, *ceteris paribus* (Fraser, Bazuin, & Hornberger, 2016; Fraser et al., 2013). Results such as these suggest that some households belonging to HOAs may adopt more intensive fertilizer use than might otherwise be consistent with their individual preferences. The policy relevance is that behavior change interventions targeted at the household level *alone* will likely meet neighborhood resistance, thereby limiting the success of fertilizer reduction strategies to mitigate environmental impacts (e.g., nitrogen export to nearby surface waters).

Additionally, *informal neighborhood-scale* influences such as social conforming pressure and cultural norms affect homeowner decisions on lawncare or landscape design (Nassauer, Wang, & Dayrell, 2009). Theoretical frameworks for informal neighborhood influences often appeal to reference group behavior theory (Holbrook, 2011; Merton & Kitt, 1950) wherein the individual homeowner conforms to surrounding neighbors. Similarly, "ecology of prestige" theory posits that decisions are influenced by the household's desire to uphold the prestige of its neighborhood and outwardly express membership in a socio-ecological lifestyle group (Grove et al., 2006). Corresponding spatial conforming influences on household fertilizer use are typically characterized in this non-economics literature using simple survey-based measures of homeowner beliefs and perceptions, for example regarding neighbors' attitudes about lawn care and neighborhood social cohesion (Carrico et al., 2018; Fraser, Bazuin, & Hornberger, 2016; Fraser et al., 2013; Martini et al., 2015).

Although this literature yields empirical insights into household behavior, approaches of this type are poorly suited to rigorous and replicable economic models of lawncare decisions. A key limitation is that spatial conforming influences are characterized in these models using survey-elicited, Likert-scale measures of homeowners' subjective beliefs, for example regarding neighbors' attitudes about lawn care. Approaches of this type are subject to well-known concerns of measurement error and endogeneity, leading to the potential for biased and inconsistent results (Hess & Beharry-Borg, 2012; Czajkowski et al. 2017). In contrast, common methods for quantifying spatial conforming effects (which can be alternatively framed as peer effects or spillovers) in the economics literature typically require *direct observations* of the behavior of interest for all spatial units in all studied areas (e.g., Beasley and Dundas 2021; Gardner and Johnston 2021; Lewis et al. 2011). Such approaches model relationships between neighboring parcels' adoption of a particular behavior, such as an agricultural best management practice, often with approaches to accommodate the potential endogeneity of behaviors observed on neighboring parcels (Lewis et al. 2011). However, the data necessary to estimate these models is almost universally unavailable for difficult-to-observe household behaviors such as fertilizer use—it is almost always infeasible to obtain data on fertilizer use or similar behaviors for *all parcels* in a neighborhood or region.

This point is especially true for studies that rely on homeowner/landowner surveys to elicit data on behaviors of interest such as fertilizer use or agricultural practice adoption—a common approach in the literature. It typically impossible to obtain a survey sample with a 100% response rate over all parcels in a studied region, thereby providing the data necessary to analyze neighborhood and/or spatial peer effects using traditional approaches in the economics literature. Hence, while informal neighborhood-scale influences are suspected to influence residential fertilizer use (and associated nonpoint source pollution emissions) in important ways, the existing literature provides no rigorous approach to model these effects.

This article builds on recent advances in the lawncare literature to construct a theoretically motivated, econometric model of household fertilizer decisions that characterizes household- and neighborhood-scale influences, estimating both informal and formal neighborhood effects. We introduce a novel methodology that leverages GIS parcel data from an existing tax-assessor database to examine informal neighborhood conforming pressures, based on quantifiable metrics of property characteristics for each respondent household relative to the surrounding neighbors. Grounded in this model, property characteristics for nearest neighbors (from tax-assessor data) relative to each surveyed household support testable hypotheses on the effects of spatial conforming effects on fertilizer decisions, along with the impacts of observable household and parcel characteristics.

We estimate these effects for two sequenced decisions for each household—whether to fertilize in a given year (binary logit), and if so with what frequency (zero-truncated negative binomial model). The two-stage specification allows us to test how household- and neighborhood-scale factors differentially affect both fertilizer decisions, and provides a means to characterize the impacts of household characteristics and spatial conforming effects (or neighborhood conforming pressures). The model is implemented using survey data from a random, address-based sample of 2,635 homeowners in the Baltimore metro region (in Maryland, USA), widely distributed across different neighborhoods. These survey data are combined with GIS parcel data from a spatially explicit tax-assessor database covering all 153,978 residential parcels in the study region (including the 2,635 homeowners who completed the survey), to construct metrics for surrounding neighbor property characteristics used to characterize spatial conforming effects. The approach allows spatial conforming effects on households' fertilizer use to be estimated via rigorous econometric models, without relying on ad hoc measurements of homeowners' perceptions or attitudes.

Our study makes several contributions to the literature. First, to our knowledge, the illustrated approach is the first rigorous model of residential lawn fertilizer decisions in the economics literature. Despite growing and high-profile attention among policymakers to the environmental impacts of residential lawn fertilizer applications (Polsky et al. 2014), modeling of these household decisions has occurred entirely outside of the economics discipline (e.g., Carrico et al., 2018; Fraser, Bazuin, & Hornberger, 2016; Fraser et al., 2013; Martini et al., 2015). The model exploits spatially explicit GIS parcel data to assess the influence on fertilizer use of property characteristics for the individual household, together with informal conforming pressures related to property characteristics of the surrounding neighborhood. Because parcel data of this type is widely available in the US and many other countries, our approach can readily applied to examine similar spatial conforming effects on fertilizer use in other regions or adapted to other lawncare and landscape behaviors (e.g., irrigation, rain garden adoption). Second, we estimate these spatial conforming effects on both the decision to fertilize and the frequency of fertilizer applications. A model specification using two disaggregated decisions allows us to test how a wide range of household-scale factors and formal and informal neighborhood-scale factors have different effects on the two different stages of the fertilizer decisions.

2. Methods

2.1 Conceptual foundation and hypotheses

The conceptual foundation for the model is relatively straightforward. We apply a method conceptually similar (though not identical) to that developed by Burkhardt et al. (2022) to measure landscape conformity for hedonic modeling, with this original approach adapted to a behavioral model of household lawncare. A simple example illustrates the underlying intuition. The social science literature provides robust empirical evidence that house age for the individual respondent is negatively associated with fertilizer use (Law et al., 2004; Zhou, Troy, & Grove, 2008). Building on this consensus, the model first estimates the effect of each household's house age on fertilizer use, *ceteris paribus*, to verify whether this negative effect occurs. Simultaneously, we estimate an additional neighborhood conforming or conforming effect on fertilizer use that might occur if a household living in an older home is surrounded by neighbors in newer homes. We hypothesize that this household will seek to conform to the behavior of newer-home neighbors by increasing fertilizer use relative to that which might otherwise occur. We hypothesize that the opposite will occur if a household living in a newer home is surrounded by neighbors in older homes.

Formalizing the approach, we specify a vector representing informal neighbor influences M_i, using property characteristics. Consider a property-characteristic variable for household i, $z_i \in Z_i$, such as house size or lot size, hypothesized to affect fertilizer use. We further specify z_j as the same variable for each surrounding neighbor's parcel j, where $j \neq i$. The corresponding neighborhood differential for household i is specified $m_i = z_i - \overline{z_j}$, where $\overline{z_j}$ is the mean of z_j for the J nearest neighbors. Considering the house-size example, $m_i > 0$ indicates that household i has a larger house than average surrounding neighbors, while $m_i < 0$ indicates that household i has a smaller house than these neighbors. Using z_i and m_i within a model predicting fertilizer application incorporates the effects of both household characteristics and conforming pressures. Similar neighborhood conforming effects may be measured for a variety of observable characteristics such as house age, house size and lot size.

Importantly, implementation of this model to characterize informal neighborhood effects does *not* require that one observe the behavior of interest (fertilizer use) for all parcels in the study region. As noted above, traditional econometric methods for quantifying spatial conforming or spillover effects require *direct observations* of the behavior of interest for all spatial units in all studied areas—so that the potential impact of the behavior observed on each parcel on nearby parcels can be estimated directly (e.g., Lewis et al. 2011; Beasley and Dundas 2021; Gardner and Johnston 2021). From a practical perspective, obtaining data of this type would be nearly impossible for a behavior such as household fertilizer use over large areas (comprising over 150,000 parcels in our case study). Instead, modeling here relies on information from widely available GIS parcel data, combined with survey data from a random sample of households obtained using address-based sampling. This approach thereby allows neighborhood effects on residential fertilizer use to be characterized using data that are widely available.

Application of the model is used to study two primary hypotheses:

1. The individual household-scale effect for property characteristics of the respondent household are expected to have significant relationships with decisions both on the probability and frequency of lawn fertilizing. Specifically, the respondent's house age and lot size will be negatively associated with the likelihood of fertilization and the number of applications conditional on fertilizing (Zhou, Troy, & Grove, 2008; Fraser et al., 2013). The respondent's house size will be positively associated with both the probability and frequency decisions.
2. The informal spatial conforming effect examines differences between property characteristics for the respondent and those of the surrounding neighbors. The sign of this effect is expected to be *opposite* of the corresponding sign in Hypothesis 1, indicating that the household is conforming to expectations and behavior of surrounding neighbors. For example, when the respondent household has a large lot size the individual effect is negative (as stated in Hypothesis 1) indicating lower fertilizer use (i.e., probability or

frequency). However, when this respondent is surrounded by neighboring households with comparatively smaller lot sizes on average (who therefore apply more fertilizer), then the respondent in turn conforms to corresponding neighborhood expectations and applies more fertilizer than they would otherwise. This central hypothesis on neighborhood conforming effects applies to each property characteristic, as explained further in the modeling framework below.

Given these two hypotheses, we anticipate that failure to understand informal spatial conforming effects linked to observable parcel characteristics will lead to misleading predictions of whether and how frequently households fertilizer their lawns—with direct implications for understanding nonpoint source pollution emissions related to residential fertilizer use.

2.2 Empirical model

Building on this conceptual framework, we model household decision-making for lawn fertilizing in two steps. Household i makes an initial binary decision d_i on whether to fertilize in a given year, with $d_i = 1$ for the household that fertilizes and $d_i = 0$ when not fertilizing. Conditional on the decision to fertilize, a subsequent frequency decision y_i is made on the number of fertilizer applications, with positive integer values $y_i = 1, 2, 3, \ldots N$ applications. The two-step structure allows household- and neighborhood-scale factors to have different effects on these two decisions. Both theory and empirical modeling suggest that this type of flexibility is needed to decompose the household decision-making process for lawn fertilization.

Household-scale variables include a vector of household demographic factors X_i, including variables characterizing household income, years residing in current home, children, pets, along with the education level, gender, and age of the household member primarily responsible for lawncare decisions. Another set of household-scale variables includes a vector of the household's property characteristics Z_i, including house size, house age, and lot size. Neighborhood-scale variables include a vector representing formal neighborhood institutions N_i, such as whether household i belongs to an HOA or neighborhood association. Neighborhood associations (NAs) are formal neighborhood-scale institutions, with the difference being that HOAs are legal entities that can levy fees to encourage or require households to adopt specific lawncare behaviors while NAs do not have legal enforcement capacity. This set of variables also distinguishes whether the HOA or NA has explicit rules regarding lawncare.

Additionally, neighborhood-scale variables include a vector representing informal neighbor influences M_i, which are constructed using the property characteristics from surrounding neighbors. Consider, for example, the property characteristic variable for household i, $z_i \in Z_i$, such as house size or lot size. We further specify z_j as the same property characteristic variable for each surrounding neighbor's parcel j, where $j \neq i$. The corresponding neighborhood differential for household i is specified as $m_i = z_i - \overline{z_J}$, where $\overline{z_J} = \frac{\sum_{j=1}^{J} z_j}{J}$ is the mean of z_j for the J nearest neighbors. Considering the example of house size, $m_i > 0$ indicates that household i has a larger house size than surrounding neighbors on average, while $m_i < 0$ indicates that household i has a smaller house size than nearby neighbors. As described below in the empirical application, we set $J = 10$, thereby defining nearest neighbors as the 10 closest homeowner parcels in Euclidean distance to each household i, as identified in the spatially explicit parcel-level tax assessor database.

The econometric model is specified as a two-part hurdle model (Cameron & Trivedi, 2005). For the first model, we use a logit specification appropriate for the binary decision to fertilize

$$d_i = 1 \;\; if \; X_i\beta + Z_i\gamma + M_i\theta + N_i\delta + \epsilon_i > 0$$

$$d_i = 0 \;\; if \; X_i\beta + Z_i\gamma + M_i\theta + N_i\delta + \epsilon_i \leq 0 \qquad (1)$$

with values of d_i=1 for a household that fertilizes and d_i=0 otherwise. The X_i, Z_i, M_i, and N_i are vectors of variables described above, with the corresponding vectors of coefficients β, γ, θ, and δ to be estimated. The error term ϵ_i represents a random component that is unobservable to the researcher, which is assumed to be independently and identically distributed with mean zero. Because each household represents one observation in the data, a panel data model such as a mixed (binary) logit is not required to accommodate multiple observations per household.

The second model analyzes the frequency of fertilizer applications, conditional on the decision to fertilize. This count variable has only positive integer values for $y_i = 1, 2, 3, \ldots N$, so a standard, zero-truncated negative binomial regression is applied (Cameron & Trivedi, 2005). With this model, the probability of observing the household i's application frequency y_i conditional on the decision to fertilize $d_i = 1$ is

$$f(y_i|d_i = 1; X_i, Z_i, M_i, N_i) = \frac{f(y_i|X_i, Z_i, M_i, N_i)}{Pr\,(d_i = 1|X_i, Z_i, M_i, N_i)} \qquad (2)$$

where the numerator $f(y_i|X_i, Z_i, M_i, N_i)$ is the unconditional likelihood for household i's application frequency, while the denominator $Pr(d_i = 1|X_i, Z_i, M_i, N_i)$ takes into account the conditional decision given that the estimation only considers households that fertilize. The corresponding vectors of parameters to be estimated in equation (2) are different from but analogous to β, γ, θ, and δ in equation (1). The unconditional likelihood has a well-known form for the negative binomial model, which is suppressed here for conciseness (Cameron & Trivedi, 2005, pp. 675-677). Estimated results may be transformed into readily interpretable marginal effects representing the influence of each independent variable on the expected number of fertilizer applications, conditional on the decision to fertilize.

2.3 Characterizing spatial conforming effects—theory and methods

This section provides theoretical intuition for the effects of both household property characteristics and spatial conforming effects (or informal neighborhood conforming pressures), grounded in the model outlined above. To simplify the exposition, we convey the theory using a simplified graphical illustration rather than via formal mathematics.[1]

Figure 1 provides an example for a setting in which the household's property characteristic z_i has an expected *positive* relationship with fertilizer use (i.e., probability and frequency). In our study, the respondent's house size z_i is hypothesized to have a positive relationship to fertilizer use (see Hypothesis 1). Hence, the corresponding informal neighborhood variable m_i for house size is hypothesized to have the *opposite* sign, with a negative relationship to fertilizer use, suggesting a neighborhood conforming effect (see Hypothesis 2). For the logit model in equation (1), this means that since the effect of house size z_i is expected to be positive ($\gamma > 0$), the corresponding effect of the informal neighborhood variable m_i for house size is expected to be negative ($\theta < 0$). The analogous effects are expected for the zero-truncated count model in equation (2), with a positive sign on house size and negative sign on the corresponding informal neighborhood variable.

For simplicity of illustration, Figure 1 displays the continuous variable on the property characteristic (e.g., house size) for the household z_i and the average for surrounding neighbors $\overline{z_j}$ in terms of a 2×2 matrix with discrete values (low/high). For example, case A shows a homogeneous neighborhood where household *i* has a small house size and is surrounded by

[1] The same theory can be conveyed via a more formal and complex mathematical structure. However, doing so yields significantly greater complexity and notation with little additional insight.

similar neighbors with small house sizes on average. Because house size is positively associated with fertilizer use (i.e., probability and frequency), then household i is expected to have low fertilizer use. The surrounding neighbors are similar with regard to house size (i.e., $m_i = 0$), and thus there is no informal neighborhood effect for this variable. In contrast, case B shows a heterogeneous neighborhood where household *i* has a small house size but is surrounded by neighbors with large house sizes (i.e., $m_i < 0$). All else equal, the surrounding neighbors with large homes in case B have higher fertilizer use than that of surrounding neighbors in case A. Hence, household *i* will have an *upward* pressure for higher fertilizer use in case B (relative to case A), in order to conform to expectations from (and behaviors of) the surrounding neighbors.

The surrounding neighbors can also create a *downward* pressure. Consider case D indicating a homogeneous neighborhood where household *i* and surrounding neighbors have large house sizes. For these circumstances, household *i* is expected to have high fertilizer use corresponding to its large house size, with no neighborhood conforming effect due to this variable because $m_i = 0$. In contrast, case C shows a heterogeneous neighborhood where household *i* has a large house size but is surrounded by neighbors with smaller homes on average (i.e., $m_i > 0$). Again all else equal, the surrounding neighbors in smaller homes in case C have lower fertilizer use than that of the neighbors in case D (Figure 1). Hence, there exists a *downward* conforming pressure on household i, leading to lower fertilizer use in case C (relative to case D).

Figure 2 provides the analogous example for the case in which the household's property characteristic z_i has a *negative* relationship with fertilizer use. For our analysis, the respondent's lot size and house age are each hypothesized to have a negative relationship to fertilizer use (Hypothesis 1). The effect of the corresponding informal neighborhood variable m_i is then hypothesized to have the opposite sign, with a positive relationship to fertilizer use (Hypothesis 2). Considering lot size applied to the graphical framework in Figure 2, for instance, case A shows a homogeneous neighborhood wherein household *i* has a small lot size and is surrounded by similar neighbors with small lot sizes. Because lot size is negatively associated with fertilizer use, the household is expected to have higher fertilizer use, with no neighborhood conforming effect for this variable because $m_i = 0$. Contrastingly, case B shows a heterogeneous neighborhood where the household has a small lot size but is surrounded by neighbors with large lot sizes (i.e., $m_i < 0$). All else equal, the surrounding neighbors with large lot sizes in case B have lower fertilizer use than that of the surrounding neighbors in case A. Therefore, household *i* will have *downward* pressure for lower fertilizer use in case B, relative to case A, to conform to surrounding neighbors. Likewise, case D represents a homogeneous neighborhood with large lot sizes for the household and surrounding neighbors, whereas case C represents a heterogeneous neighborhood where the household has a large lot but is surrounded by neighbors with small lot sizes (i.e., $m_i > 0$). Hence, the household will have an *upward* pressure for higher fertilizer use in case C relative to case D.

The same hypothesized effects for lot size in Figure 2 described above are applicable to house age. For instance, case A represents a homogeneous neighborhood with new homes (low value for house age) for the household and surrounding neighbors, while case B represents the household with a new home surrounded by neighbors with older homes. All else equal, the household in case A has higher fertilizer use, while the household in case B will have a *downward* pressure on fertilizer use relative to case A, due to the informal neighborhood conforming effect for this variable. The hypotheses outlined using Figures 1 and 2 will be tested empirically in the estimation results below.

One important dimension of the illustrated approach to modeling spatial conforming effects on household behaviors is that it obviates problems of endogeneity that can affect traditional approaches in the economics literature. Common models of spatial spillovers or conforming effects in the economics literature typically rely on observed relationships between of the same modeled behavior across neighboring parcels. However, approaches of this type can lead to endogenous explanatory variables within an econometric model, for example if an unobserved characteristic simultaneously influences the same behavior on neighboring parcels or due to various types of "mirroring" or reverse causation (Gardner and Johnston 2021). Additional statistical procedures are then required to address this endogeneity (Lewis et al. 2011; Beasley and Dundas 2021). Here, however, spatial conforming effects are characterized using temporally exogenous variables on parcel and housing characteristics observed across neighboring parcels, thereby providing a means to model these effects without the endogeneity concerns that can apply to alternative modeling approaches.

3. Data

3.1 Household survey development and sampling design

Data for the analysis were derived from a large-sample household push-to-web survey, integrated with parcel (tax-assessor) data as outlined above. We conducted the survey in the City of Baltimore and Baltimore County in Maryland (USA) to collect information on household-level fertilizer use and lawncare practices, along with data on household and property characteristics. Nitrogen is the primary nutrient of concern linked to household fertilizer use in our study region, since phosphorus is banned for household fertilizer in Maryland. Understanding household and neighborhood drivers for fertilizer decisions is highly policy relevant since nitrogen nonpoint source pollution is the most challenging nutrient to address to comply with the Chesapeake Bay total maximum daily load requirements, as well as nitrogen impacts on other ecosystem services.

The survey was developed over a three-year process, in coordination with scientists from the Baltimore Ecosystem Study Long-Term Ecological Research site, with further input from academics, local government officials, and extension agents involved with residential lawn fertilizer and stormwater management in the Baltimore region. Six focus groups were conducted to improve the survey design, and then pilot tested among approximately 40 Maryland homeowners to ensure clarity of survey questions. These and other aspects of survey design followed best practice guidelines (Dillman, Smyth, & Christian, 2014; Johnston et al., 2017).

The sample of single-family homeowners in Baltimore City and County was drawn randomly from the complete spatially explicit parcel-level tax assessor database from the Maryland Tax and Assessment Office. The database was initially screened to select single-family, owner-occupied households with parcel lot sizes from 0.1 to 5 acres. To ensure that the property had an existing lawn, we spatially overlaid high-resolution (one meter) land cover data from the Chesapeake Conservancy with the parcel boundary map and selected parcels with at least 250 square feet of lawn area. After screening, this yielded a total population of 153,978 households in the study region, from which a random sample of 30,000 households was drawn for the survey.

The survey was implemented during November - December 2019 using a mixed-mode, push-to-web approach. Participation was solicited through mailed invitation letters that provided the website link to an online survey in Qualtrics. The mailed letter included a unique identification number and password for each household that allowed us to link the survey data spatially to the household address. The initial invitation letter was followed, at weekly intervals, by a reminder post card and final reminder letter. To increase response rates, those taking the survey were entered in a raffle for one of three $500 gift cards. Responses were received from a total of 3,836 households (12.8% response rate). The final sample size for model estimation was 2,635 respondents, after accounting for item non-response on survey questions used as dependent and explanatory variables in the estimated models (respondents were permitted to leave questions blank if desired).

3.2 Model variables

The dependent variables for analysis were derived from the survey questions asking the respondent to report the number of fertilizer applications done in the past year by the household or a professional. The survey question on the number of fertilizer applications was asked separately for the front and back yard. This was done following prior studies (e.g., Fraser, Bazuin, & Hornberger, 2016; Law, Band, & Grove, 2004), considering that front yards might have higher lawn fertilizer use than back yards because the front lawn is more visible to neighbors. Interestingly, the vast majority of households reported the same number of fertilizer applications in the front and back yard. The crosstabulation in the Appendices (Table A) shows that 92.1% (2,426 out of 2,635 households) had the same fertilizer frequency in the front and back yard.

For this reason, the annual fertilizer frequency was calculated at the property level based on the average of front and back yard frequency. This average frequency was rounded up to the integer value for the small number of respondents where frequencies were not equal. Hence, the binary dependent variable d_i equals zero when the household did not fertilize the front and back yard, and otherwise equals one. The dependent variable y_i is equal to the average frequency, which has integer values needed for the zero-truncated negative binomial model.

The survey elicited household demographic characteristics X_i, including the respondent's age, gender, highest degree of education, years living in current home, and annual gross household income. The survey also asked whether any children live at home and whether there are pets who spend time outdoors on the property. The questionnaire further collected information on formal neighborhood governance status N_i where the homeowner resides—whether it belongs to an HOA or NA. For those respondents who indicated membership in either an HOA or NA, the questionnaire then asked whether the association had explicit rules pertaining to lawn care or appearance.

Data on property characteristics Z_i was available and taken directly from the parcel-level tax assessor database. Specifically, we used the property lot size in acres from the parcel boundary shapefile. We used the housing characteristics for the house age in years and house size converted into units of 1,000 square feet. The database was also used to construct corresponding variables on the differences in property characteristics M_i between the respondent household and their ten nearest neighbors (using Euclidean distance from the respondent parcel centroid). We chose ten nearest neighbors as a compromise to balance two competing goals—ensuring sufficient neighbors to construct a stable mean representative of neighborhood property characteristics while not including too many neighbors so far away that they have little influence.

It is important to recognize that our dataset has 2,635 survey respondents and 153,978 households in our study region (i.e., single-family homeowner neighbors used to construct M_i). A novel contribution of our methodology is that we leverage the tax-assessor database to construct measures of property characteristics for the nearest neighbors to each respondent household, even if none of these nearest households took the survey. The 2,635 survey respondents are thus primarily located in different neighborhoods, thereby providing a large sample size to examine informal neighborhood conforming effects across the study region. As introduced above, the approach allows spatial conforming effects on household behavior to be estimated without observing the behavior of interest (here, fertilizer use) for all parcels in the study area. Because parcel-level tax assessor data has become more widely available, this approach can readily be adapted in other regions.

4. Results

Table 1 provides summary statistics for the dependent and explanatory variables used in the estimated models. The binary dependent variable on whether the household fertilizes has a mean of 0.52, indicating that about 48% of respondent households did not apply fertilizer to their lawns. For those who fertilized, the average frequency is 2.5 times per year with a range of 1 to 12 times per year. Marginal effects from both the logit (Model I) and zero-truncated negative binomial (Model II) regressions are displayed in Table 2. Marginal effects are presented rather than parameter estimates because the former are more readily interpreted as predicted changes in the dependent variables. Equivalent model results with the untransformed parameter estimates are included in the Appendices (Table B). Both model stages show good fit to the data, and model variables are jointly significant at $p < 0.001$ ($\chi^2 = 304.2$, df. = 22 for Model I, $\chi^2 = 140.6$, df. = 22 for Model II). When marginal effects are statistically significant in Table 2, the signs of these effects correspond with expectations derived from theory and are largely consistent with prior empirical findings.

We organize the discussion of model results around the different categories of variables and effects incorporated in the model, beginning with effects of common household characteristics often included in models of household fertilizer use. We then proceed to consider effects of formal neighborhood organizations (such as HOAs), and then the parcel and accompanying spatial conforming effects that are the primary emphasis of the analysis.

4.1 Household characteristics

Comparison of results for Models I and II on household demographic characteristics suggests the importance of disaggregating the two stages of fertilizing decisions. Table 2 shows that some household variables have significant effects on one fertilizer decision, but not the other decision. For example, senior citizens (age over 65 years) are significantly more likely to fertilize (Model I). However, conditional on the decision to fertilize, senior citizens do not have a significantly higher fertilizer frequency compared to other respondents (Model II). Results in Table 2 further indicate that male respondents are more likely to fertilize than female respondents, while there is no significant difference in the application frequency.

The results on annual household income show that households in the highest income class (>=$200,000) generally have higher likelihood and application frequency than lower income classes. In Model I, the lowest income class (<$25,000) has 0.18 lower probability of fertilizing relative to the highest income class, which serves as the baseline category. This suggests that the effect of income on purchasing household goods, such as fertilizer, is most significant for the lowest income class regarding the decision on whether to fertilize. Conditional on fertilizing, the highest income class has a significantly higher application frequency than other income classes, ranging from 0.6 to 1.0 more applications per year. Results further indicate that the number of years living in the current residence has a significantly positive relationship with both the probability and frequency of lawn fertilization. The respondent's education level does not have a significant effect on either fertilizer decision. Further, the two indicator variables for children at home or pets spending time outdoors do not have a significant influence in either Model I or II.

4.2 Formal neighborhood characteristics

In order to identify informal spatial conforming effects, one must control for potentially confounding effects of formal neighborhood organizations such as HOAs and NAs. The model accommodates formal meso-scale lawncare influences as a function of each household's membership in an HOA or NA, and if so whether these organizations have explicit rules on lawncare. Results in Table 2 show that the probability of fertilizing increases by about 0.13 if the household belongs to an HOA, compared to the baseline category (i.e., neither HOA nor NA). We find no significant additional effect on the probability of fertilizing for households belonging to HOAs with explicit rules on lawncare, compared to those households in HOAs without such rules. Conditional on the decision to fertilize, households in HOAs have higher fertilizer frequency relative to those households in neither HOAs nor NAs. This effect on fertilizer frequency is somewhat moderated for HOAs with rules, albeit at the 10% significance level. Our results are largely consistent with recent papers (Fraser, Bazuin, & Hornberger, 2016; Fraser et al., 2013), who similarly find that households in HOAs have higher probability and/or application rates for lawn fertilization.

The results indicate that households in an NA had similar likelihood of fertilizing compared to the baseline households in neither an HOA nor NA. Yet households in NAs with explicit lawncare rules had a significantly higher probability of fertilizing. In fact, the magnitude and significance of the increased probability for households in NAs with rules (0.14) is approximately the same as those households in HOAs with or without rules (0.13). With respect to fertilizing frequency conditional on the decision to fertilize, households tend to fertilize more often if they are affiliated with either an HOA or NA. The HOA effect is over twice as large—a household is expected to fertilize roughly 0.7 more times per year if it belongs to an HOA, and 0.3 more times per year if it belongs to an NA, *ceteris paribus*. Our results suggest that NAs have some significant influence on household fertilizing decisions, though perhaps less than HOAs, as expected in Hypothesis 3. This is a unique finding since similar analysis on NAs done in the Baltimore region (Fraser et al., 2013) did not find significant effects for NAs on household fertilizer decisions. One potential reason is that our sample size and random design allowed these effects to be estimated with greater statistical power.[2]

4.3 Property characteristics

Results in Table 2 indicate that all three primary property (or parcel) characteristics have statistically significant marginal effects for both Models I and II, with expected relationships as outlined in Hypothesis 1. Consider results for Model I on the probability of fertilizing, where all three results are highly significant ($p < 0.001$). House age has a negative relationship with the likelihood of fertilizing, indicating that households in newer homes are more likely to fertilize than those in older homes. Home size has a positive relationship with the decision to fertilize. These results are expected since newer larger homes often have topsoil removed during recent land development and lawns take time to mature and develop suitable root systems. Lot size is negatively related to the likelihood of fertilizing, which is anticipated given the additional effort

[2] For example, Fraser et al. (2013) implemented stratified random sampling, collecting 498 observations across 30 neighborhoods (9 HOAs, 14 NAs, and 7 in neither). Our sampling design selected households randomly, such that the 2,635 respondents are widely distributed across neighborhoods throughout the Baltimore metro region. Our design thus provided a larger and more widespread sample of household data for analysis, thereby supporting greater statistical power for the analysis.

and cost required to apply fertilizer across a larger lot area (Fraser et al., 2013). Conditional on the initial decision to fertilize, the subsequent decision on the application frequency in Model II shows that all three property characteristics have marginal effects significant at the 5% level or better. Households with newer larger homes have higher fertilizer frequency, consistent with a commonly observed pattern in which suburban areas in the Baltimore metro region with newer larger homes tend to have prominent lawns and industrial lawncare practices.

4.4 Spatial conforming effects (informal neighborhood characteristics)

The primary focus on the model is to estimate informal, spatial conforming effects on fertilizer use, after controlling for the variables discussed above. We expect these informal spatial conforming effects to have opposite signs compared to the companion estimates for the corresponding household-level property characteristic effects, as stated in Hypothesis 2 and outlined in the modeling framework. Results in Table 2 support these expectations for the opposite sign in all six cases; however, these informal neighborhood conforming effects are only found to be significant for the initial decision on the probability of fertilizing in Model I. The marginal effects on the subsequent frequency decision have the expected signs but are not statistically significant in Model II.

As anticipated, the marginal effect is positive for the difference in house age variable (Model I). This suggests that a newer house built in an older neighborhood would have lower likelihood of fertilizing to conform to expectations of surrounding neighbors with older homes, compared to a case in which the newer house is built with similar neighbors in newer homes ($p < 0.001$). Interestingly, this implies a *downward* pressure on whether to fertilize, since the household in the newer house is conforming to surrounding neighbors in older homes.

Importantly, our results suggest that conforming neighborhood pressure can operate either in an upward or downward direction. Although this is an intuitive finding, it stands in contrast to past theories of neighborhood effects, that tend to emphasize only upward pressures on fertilizer use.[3] The marginal effect is similarly positive for the difference in lot size variable in Model I ($p < 0.001$). This implies that a household on a large lot size has a higher likelihood of fertilizing when surrounded by neighbors on smaller lots, as compared to the same household when the surrounding neighbors have similar larger lot sizes. The marginal effect is negative for the difference in house size variable in Model I, albeit significant at a lower 10% level.

The significance of the marginal effects for only Model I on the initial binary decision on whether to fertilize and not the subsequent frequency decision in Model II is plausibly intuitive, based on the conceptual expectation for how informal conforming effects might arise across a neighborhood. The initial fertilizing decision among neighbors is readily observable based on whether one tends to see their neighbors engage in fertilizer use. This behavioral observability provides a greater capacity to mirror neighborhood behaviors because one can see these behaviors readily. In contrast, the average number of fertilizer applications per household across a neighborhood is more difficult to deduce based on casual observations—and thereby less apt to be mirrored by each household.

5. Discussion and conclusions

This study builds on recent advances in the lawncare literature to estimate a large-sample statistical model of household fertilizing behavior for household- and neighborhood-scale factors, with an emphasis on informal and formal neighborhood components. The model is

[3] For example, the social science "ecology of prestige" theory emphasizes upward pressures for more intensive lawncare to maintain or increase socio-economic status (Grove et al. 2006).

estimated for two sequenced decisions faced by households: whether to fertilize, and if so with what frequency. We find it essential to disaggregate household decision making into two stages, since the estimation results in Models I and II indicate that several household demographic and informal neighborhood variables are significant for one decision but not the other.

Among the primary innovations of the analysis is a novel approach to estimate informal neighborhood conforming effects based on quantifiable metrics that exploit observable property characteristics for the respondent relative to surrounding neighbors, including those nearby who did not take the survey. This approach carries multiple advantages, including lower data requirements than common economic approaches to estimate spatial conforming effects and avoidance of common endogeneity challenges in these models. Simultaneously, they avoid challenges of endogeneity and measurement errors common in approaches published outside of the economics literature.

Results of the model suggest that respondents' property characteristics exert highly significant influences on both fertilizer decisions. Informal neighborhood effects are significant for the initial decision on whether to fertilize but not the subsequent frequency decision, presumably because the former is more observable to surrounding neighbors than the latter. The effects of formal neighborhood characteristics are significant in both stages, particularly for households residing in HOAs. That said, only approximately 11% of households live in an HOA, while the majority of households reside in areas without HOAs and NAs in the Baltimore metro region.

Estimation results on individual and neighboring property characteristics imply strong forces for homogeneity at the neighborhood level. It is intuitive that similar fertilizer use would occur within a homogeneous neighborhood, for example, where all homes were built at the same time with similar home sizes and lot sizes. Our results, however, further suggest homogeneity in fertilizer use occurs to some extent even in heterogeneous neighborhoods with homes of different vintages and sizes, due to the upward and downward conforming effects to meet surrounding neighbors' expectations. Our findings on informal neighborhood conforming effects are analogous to Nassauer, Wang, and Dayrell (2009), except those authors find conforming effects for landscape design features in front yards using hypothetical experimental data while we analyze actual household fertilizer use exploiting parcel-level tax assessor data to analyze neighborhood variation in property characteristics in the real world.

While our results on informal conforming effects suggest influences toward homogeneity at the neighborhood level, substantial heterogeneity in fertilizer use exists across urban, suburban, and exurban areas within the Baltimore region. The parcel-level tax assessor data, for instance, reveals a wide range of neighborhoods that vary in property and housing characteristics. As in many cities, the Baltimore metro region developed from inward to outward, where smaller older homes were typically built in the City of Baltimore and inner suburbs within the Beltway while newer larger homes were built in the outer suburban and exurban areas (Hanlon and Vicino, 2007). Hence, efforts to target fertilizer reduction should recognize that fertilizer use is higher in outer suburbs and exurbs where newer larger homes are prevalent, even though many nonprofit organizations focus on the high population centers in the urban core. Moreover, strategies for fertilizer reduction should be organized at the neighborhood level, since informal neighborhood conforming effects are likely to stymie efforts targeted solely at the individual-household level.

Previous studies have often analyzed household fertilizer decisions as a function of housing values (Carrico et al., 2018; Fraser, Bazuin, & Hornberger, 2016; Fraser et al., 2013).

We choose instead to use the housing and property characteristics that are the foundational components of housing values for two reasons. First, prior studies argue that housing value serves as a proxy for income. In our analysis, we elicit household income data in the survey and incorporate this variable into the analysis directly. Second, housing value is a function of housing and property characteristics. As known in hedonic price theory and empirical applications, housing values typically increase with home size and lot size, while decreasing with home age (Cho et al., 2009; Noh, 2019). While the respondent's housing value may be assumed to be positively related to fertilizer use, it is important to decompose the effects of the individual housing and property characteristics. For instance, house size is expected to have a positive relationship with house value and positive relationship to fertilizer use. In contrast, lot size is expected to have a positive relationship with house value but negative relationship to fertilizer use. Therefore, the housing value combines and confounds these relationships and thus it is more robust to separate the effects on fertilizer use for the fundamental components for housing and lot characteristics.

Several caveats and limitations must be acknowledged when interpreting the results presented here. First, the survey data used for our analysis relies on self-reported household fertilizer use. While we made efforts to obtain accurate information (e.g., pretesting the survey to evaluate respondents' confidence in their answers), self-reported data inherently may be prone to recall bias. We also utilize the frequency of applications as a correlate of fertilizer intensity in Model II, instead of directly attempting to obtain the fertilizer application rate. This was due to feedback from focus groups, which revealed clearly that households were more confident reporting the number of applications in the past year, while households were typically unable to quantify application rates or were able to do so only with considerable hesitation and uncertainty.

Prior studies that conducted in-person interviews to obtain such data have often reported missing information or uncertain data from households, requiring imputation methods to calculate application rates (Carrico et al., 2018; Fraser et al., 2013). To avoid these challenges, we opted to collect fertilizer frequency in the online survey rather than application rates. Second, as in all models of this type, simplifications and assumptions are required to promote tractability. For example, while we have a wide range of household- or neighborhood-scale factors, we do not measure all possible characteristics that might be used to quantify possible impacts on fertilizing behavior. Moreover, although the modeling framework can be readily extended to other regions, further research is required to assess whether and how similar empirical findings apply to different regions or populations.

These and other caveats aside, the results presented above provide empirical evidence that alternative approaches to measuring informal neighborhood (or spatial conforming) influences can provide novel insights into how households make fertilizing decisions. Predictions of this type can be directly coupled to biophysical hydrological or nutrient transport models to predict implications for nonpoint emissions to water bodies (e.g., Johnston et al. 2022). By leveraging spatially parcel-level tax assessor data that is widely available, the approach can be readily applied to create the random sample of households for survey implementation and to construct metrics for household and neighborhood characteristics. Further research opportunities should be pursued to apply this approach in other regions to various household behaviors, such as tree planting, irrigation, and adoption of stormwater management practices.

References

Beasley, W.J. & Dundas, S.J. (2021). Hold the line: Modeling private coastal adaptation through shoreline armoring decisions. *Journal of Environmental Economics and Management.* 105, 102397.

Burkhardt, J., Chan, N.W., Bollinger, B. and Gillingham, K.T. (2022). Conformity and Conservation: Evidence from Home Landscaping and Water Conservation. American Journal of Agricultural Economics 104, 1, 228-248.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications*. Cambridge university press.

Carrico, A. R., Fraser, J., & Bazuin, J. T. (2013). Green with envy: Psychological and social predictors of lawn fertilizer application. *Environment and Behavior,* 45(4), 427-454.

Carrico, A. R., Raja, U. S., Fraser, J., & Vandenbergh, M. P. (2018). Household and block level influences on residential fertilizer use. *Landscape and Urban Planning,* 178, 60-68.

Cho, S., Clark, C., Park, W., Kim, S. (2009). Spatial and temporal variation in the housing market values of lot size and open space. *Land Economics*, 85(1), 51-73.

Chowdhury, R. R., Larson, K., Grove, M., Polsky, C., Cook, E., Onsted, J., & Ogden, L. (2011). A multi-scalar approach to theorizing socio-ecological dynamics of urban residential landscapes. *Cities & the Environment (CATE),* 4(1), 1-19.

Cook, E. M., Hall, S. J., & Larson, K. L. (2012). Residential landscapes as social-ecological systems: A synthesis of multi-scalar interactions between people and their home environment. *Urban Ecosystems*, 15(1), 19-25.

Czajkowski, M., Hanley, N., & Nyborg, K. (2017). Social norms, morals and self-interest as determinants of pro-environment behaviours: the case of household recycling. *Environmental and Resource Economics, 66*(4), 647-670.

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, phone, mail, and mixed-mode surveys: The tailored design method*. John Wiley & Sons.

Fraser, J., Bazuin, J. T., & Hornberger, G. (2016). The privatization of neighborhood governance and the production of urban space. *Environment and Planning A: Economy and Space,* 48(5), 844-870.

Fraser, J. C., Bazuin, J. T., Band, L. E., & Grove, J. M. (2013). Covenants, cohesion, and community: The effects of neighborhood governance on lawn fertilization. *Landscape and Urban Planning,* 115, 30-38.

Fuentes, T. L. (2021). Homeowner preferences drive lawn care practices and species diversity patterns in new lawn floras. *Journal of Urban Ecology,* 7(1), 1-13.

Gardner, G. & Johnston R.J. (2021). Is shoreline armoring a response to marsh migration? Modeling relationships between coastal marshes and private adaptation decisions. *Water Resources and Economics* 36, 100187.

Grove, J. M., Troy, A. R., O'Neil-Dunne, J. P., Burch, W., Cadenasso, M., & Pickett, S. (2006). Characterization of households and its implications for the vegetation of urban ecosystems. *Ecosystems,* 9(4), 578-597.

Hanlon, B., & Vicino, T. (2007). The fate of inner suburbs: Evidence from metropolitan Baltimore. *Urban Geography*, 28(3), 249-275.

Hess, S., & Beharry-Borg, N. (2012). Accounting for latent attitudes in willingness-to-pay studies: the case of coastal water quality improvements in Tobago. *Environmental and Resource Economics, 52*(1), 109-131.

Holbrook, M. B. (2001). Market clustering goes graphic: The Weiss trilogy and a proposed extension. *Psychology & Marketing* 18, 67-85.

Johnston, R. J., Boyle, K. J., Adamowicz, W., Bennett, J., Brouwer, R., Cameron, T. A., Hanemann, W. M., Hanley, N., Ryan, M., & Scarpa, R. (2017). Contemporary guidance for stated preference studies. *Journal of the Association of Environmental and Resource Economists,* 4(2), 319-405.

Johnston, R. J., Ndebele, T., & Newburn, D. A. (2022). Modeling transaction costs in household adoption of landscape conservation practices. *American Journal of Agricultural Economics*, 1-27.

Johnston, R.J., Newburn, D.A., Wang, H., Ndebele, T. and Nolte, C. 2022. Residential Lawn Fertilizer Use and Nitrogen Loading Intensity Across the Long Island Sound Watershed. Long Island Sound Research Conference, Bridgeport, CT. May 18.

Larson, K. L., Andrade, R., Nelson, K. C., Wheeler, M. M., Engebreston, J. M., Hall, S. J., Avolio, M. L., Groffman, P. M., Grove, M., & Heffernan, J. B. (2020). Municipal regulation of residential landscapes across US cities: Patterns and implications for landscape sustainability. *Journal of Environmental Management,* 275, 111132.

Larson, K. L., & Brumand, J. (2014). Paradoxes in landscape management and water conservation: Examining neighborhood norms and institutional forces. *Cities and the Environment (CATE),* 7(1), 6.

Larson, K. L., Nelson, K. C., Samples, S., Hall, S. J., Bettez, N., Cavender-Bares, J., Groffman, P. M., Grove, M., Heffernan, J. B., & Hobbie, S. E. (2016). Ecosystem services in managing residential landscapes: Priorities, value dimensions, and cross-regional patterns. *Urban Ecosystems,* 19(1), 95-113.

Law, N., Band, L., & Grove, M. (2004). Nitrogen input from residential lawn care practices in suburban watersheds in Baltimore County, MD. *Journal of Environmental Planning and Management,* 47(5), 737-755.

Lewis, D. J., Barham, B. L., & Robinson, B. (2011). Are there spatial spillovers in the adoption of clean technology? The case of organic dairy farming. *Land Economics*, 87(2), 250-267.

Locke, D. H., Polsky, C., Grove, J. M., Groffman, P. M., Nelson, K. C., Larson, K. L., Cavender-Bares, J., Heffernan, J. B., Chowdhury, R. R., & Hobbie, S. E. (2019). Residential household yard care practices along urban-exurban gradients in six climatically-diverse US metropolitan areas. *PloS One,* 14(11), e0222630.

Martini, N. F., Nelson, K. C., Hobbie, S. E., & Baker, L. A. (2015). Why “feed the lawn”? Exploring the influences on residential turf grass fertilization in the Minneapolis−Saint Paul metropolitan area. *Environment and Behavior,* 47(2), 158-183.

Merton, R. K., & Kitt., A. (1950). *Contributions to the theory of reference group behavior*. Free Press, Glencoe, IL.

Milesi, C., Running, S. W., Elvidge, C. D., Dietz, J. B., Tuttle, B. T., & Nemani, R. R. (2005). Mapping and modeling the biogeochemical cycling of turf grasses in the United States. *Environmental Management,* 36(3), 426-438.

Nassauer, J. I., Wang, Z., & Dayrell, E. (2009). What will the neighbors think? Cultural norms and ecological design. *Landscape and Urban Planning,* 92(3-4), 282-292.

Newburn, D. A., & Alberini, A. (2016). Household response to environmental incentives for rain garden adoption. *Water Resources Research,* 52(2), 1345-1357.

Noh, Y. (2019). Does converting abandoned railways to greenways impact neighboring housing prices? *Landscape and Urban Planning,* 183, 157-166.

Polsky, C., Grove, J. M., Knudson, C., Groffman, P. M., Bettez, N., Cavender-Bares, J., Hall, S. J., Heffernan, J. B., Hobbie, S. E., & Larson, K. L. (2014). Assessing the homogenization of urban land management with an application to US residential lawn care. *Proceedings of the National Academy of Sciences,* 111(12), 4432-4437.

Sisser, J. M., Nelson, K. C., Larson, K. L., Ogden, L. A., Polsky, C., & Chowdhury, R. R. (2016). Lawn enforcement: How municipal policies and neighborhood norms influence homeowner residential landscape management. *Landscape and Urban Planning,* 150, 16-25.

Tran, L., McCann, L., & Shin, D. W. (2020). Determinants of households' adoption of organic pesticides for lawns and gardens. *Journal of Environmental Protection,* 11(4), 269-298.

Zhou, W., Troy, A., & Grove, M. J. (2008). Modeling residential lawn fertilization practices: Integrating high resolution remote sensing with socioeconomic data. *Environmental Management*, 41, 742-752.

Table 1. Variable definitions and summary statistics

Variable Type	Variable	Mean	S.D.	Min.	Max.
Dependent variable (d_i)	Fertilize lawn (yes=1)	0.521	0.500	0	1
Dependent variable (y_i)	Fertilizer application frequency conditional on fertilizing	2.474	1.711	1	12
Household factors (X_i)	Annual gross household income				
	< $25,000	0.026	0.159	0	1
	$25,000 - $49,999	0.080	0.271	0	1
	$50,000 - $99,999	0.282	0.450	0	1
	$100,000 - $199,999	0.361	0.480	0	1
	>= $200,000	0.133	0.340	0	1
	I'd rather not report	0.118	0.322	0	1
	Years of living in current home	17.64	13.14	1	95
	Pets spending time outdoors (yes=1)	0.500	0.500	0	1
	Gender (male=1)	0.652	0.477	0	1
	Age over 65 (yes=1)	0.290	0.454	0	1
	Have children (yes=1)	0.388	0.487	0	1
	Highest degree of education				
	No college	0.286	0.452	0	1
	College	0.320	0.467	0	1
	Advanced degree	0.394	0.489	0	1
Property factors (Z_i)	Lot size (acres)	0.554	0.770	0.100	5.000
	House age (years)	58.71	27.52	2	219
	House size (1,000 square feet)	1.955	0.866	0.640	7.411
Informal neighborhood factors (M_i)	Difference in lot size	0.032	0.420	-2.099	3.699
	Difference in house age	0.713	16.65	-71.50	137.9
	Difference in house size	0.007	0.550	-2.299	3.829
Formal neighborhood factors (N_i)	HOA (yes=1)	0.113	0.316	0	1
	HOA with lawncare rules (yes=1)	0.083	0.276	0	1
	NA (yes=1)	0.269	0.444	0	1
	NA with lawncare rules (yes=1)	0.042	0.201	0	1
	Neither HOA nor NA	0.618	0.486	0	1

Sample size N=2,635.

Table 2. Marginal effects for logit (model I) and zero-truncated negative binomial (model II) regressions

	Variable	Model I		Model II	
		Fertilize (yes/no)		Fertilizer frequency conditional on fertilizing	
Household effect (X_i)	Annual household income (Baseline: >= $200,000)				
	< $25,000	-0.178***	(0.067)	-0.808*	(0.435)
	$25,000 - $49,999	-0.079*	(0.047)	-0.677**	(0.289)
	$50,000 - $99,999	-0.067*	(0.036)	-1.020****	(0.213)
	$100,000 - $199,999	-0.047	(0.032)	-0.614***	(0.198)
	I'd rather not report	-0.044	(0.040)	-0.661***	(0.227)
	Years of living in home	0.002**	(0.001)	0.020***	(0.005)
	Pets outdoors (yes=1)	-0.019	(0.019)	-0.169	(0.111)
	Gender (male=1)	0.066***	(0.020)	0.084	(0.123)
	Age over 65 (yes=1)	0.054**	(0.025)	-0.006	(0.143)
	Have children (yes=1)	0.011	(0.021)	-0.041	(0.125)
	Highest degree of education (Baseline: Advanced degree)				
	No college	0.029	(0.025)	-0.041	(0.144)
	College degree	-0.010	(0.022)	-0.043	(0.126)
Property effect (Z_i)	Lot size (acre)	-0.118****	(0.019)	-0.249**	(0.109)
	House age (years)	-0.004****	(0.001)	-0.014****	(0.003)
	House size (1,000 square feet)	0.092****	(0.019)	0.208**	(0.093)
Informal neighborhood effect (M_i)	Difference in lot size	0.111****	(0.030)	0.122	(0.182)
	Difference in house age	0.002****	(0.001)	0.007	(0.005)
	Difference in house size	-0.040*	(0.023)	-0.033	(0.116)
Formal neighborhood effect (N_i)	HOA and NA affiliation (Baseline: Neither HOA nor NA)				
	HOA (yes=1)	0.131**	(0.062)	0.709***	(0.241)
	HOA with rules (yes=1)	-0.026	(0.072)	-0.504*	(0.262)
	NA (yes=1)	0.016	(0.023)	0.291**	(0.140)
	NA with rules (yes=1)	0.145***	(0.051)	0.170	(0.238)
	Log likelihood	-1,672		-2,213	
	Chi-square	304.2 (df. = 22)		140.6 (df. = 22)	
	Prob > Chi-square	0.000		0.000	
	Number of observations	2,635		1,372	

Standard errors in parentheses. **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1.

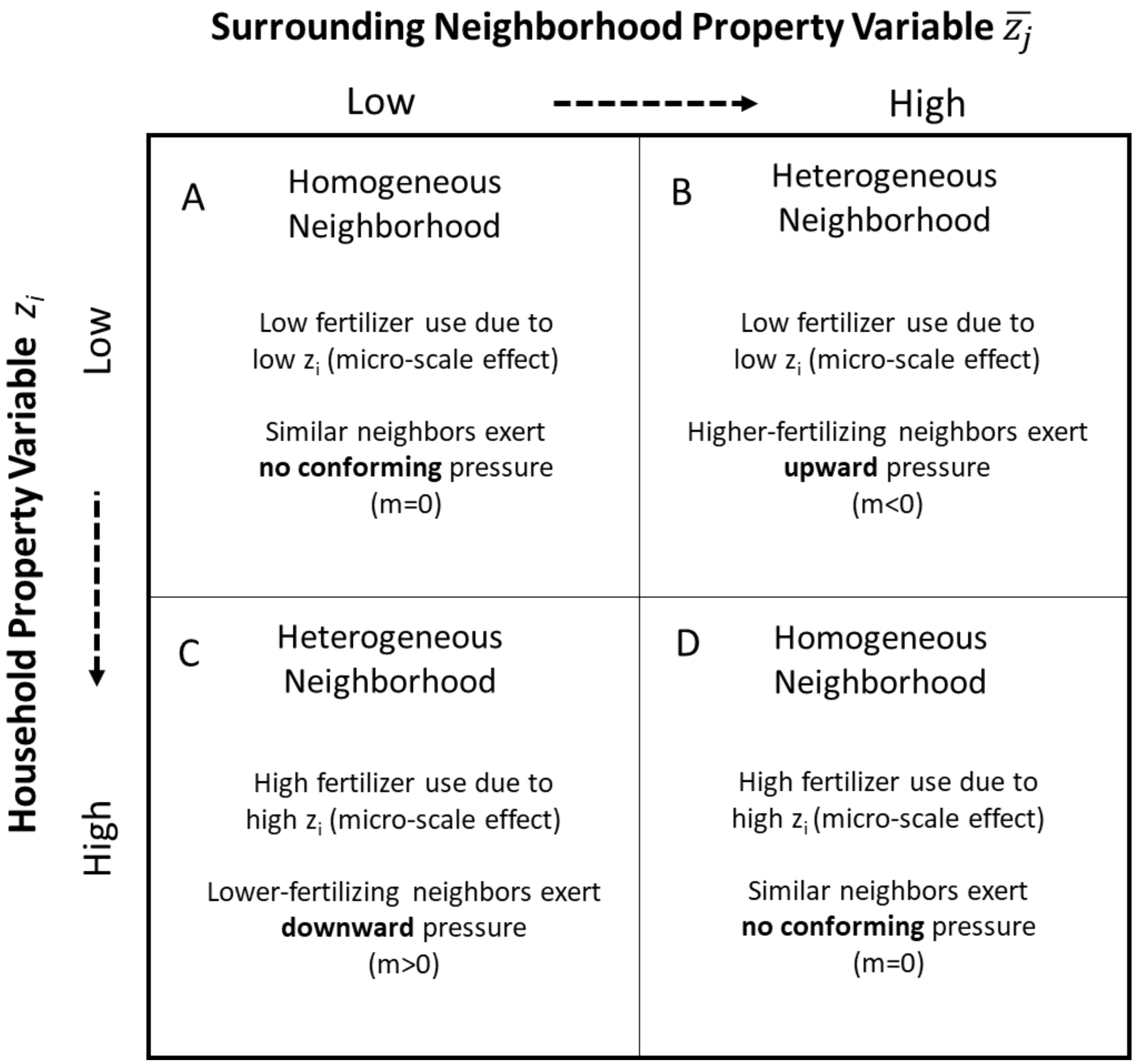

Figure 1. Conceptual model when fertilizer use has expected *positive* relationship with household property variable (e.g., house size)

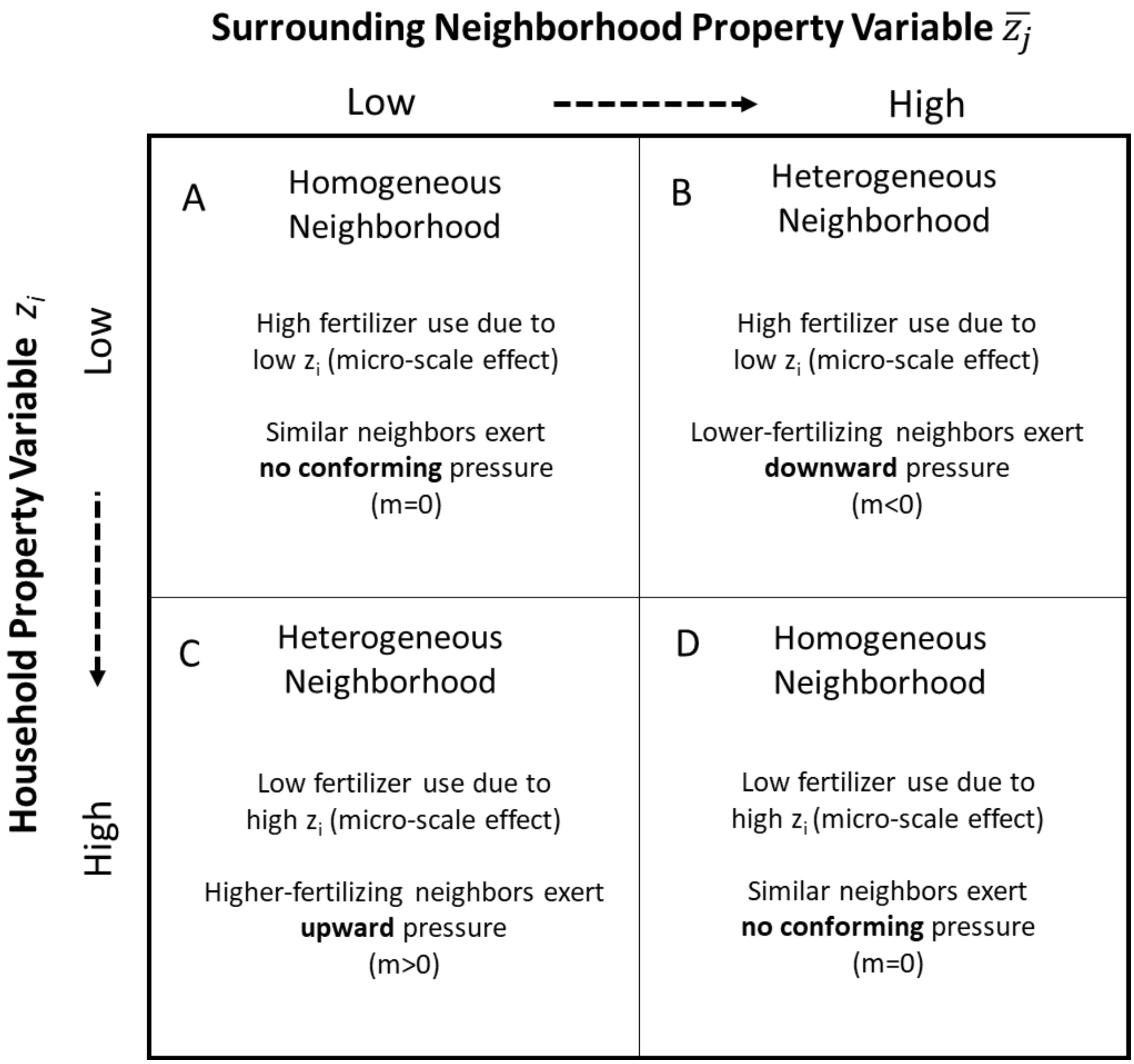

Figure 2. Conceptual model when fertilizer use has expected *negative* relationship with household property variable (e.g., lot size, house age)

Appendices

Table A. Cross-tabulation for the fertilizer frequency on the front and back lawn

Fertilizer frequency on the front lawn	Fertilizer frequency on the back lawn								
	0	1	2	3	4	5	6	>=7	Total
0	1,263	24	2	1	1	0	0	1	1,292
1	60	408	15	0	0	0	0	0	483
2	19	25	303	4	1	0	0	1	353
3	9	1	4	137	3	0	0	0	154
4	11	4	4	6	157	1	0	0	183
5	3	0	2	0	0	58	0	0	63
6	4	0	1	0	0	0	69	1	75
>=7	0	0	0	1	0	0	0	31	32
Total	1,369	462	331	149	162	59	69	34	2,635

Note: The correlation coefficient for the fertilizer frequency on the front and back lawn is 0.928.

Table B. Coefficient estimates for logit (model I) and zero-truncated negative binomial (model II) regressions

	Variable	Model I		Model II	
		Fertilize (yes/no)		Fertilizer frequency conditional on fertilizing	
Household effect (X_i)	Annual household income (Baseline: >= $200,000)				
	< $25,000	-0.802***	(0.310)	-0.302	(0.239)
	$25,000 - $49,999	-0.355*	(0.210)	-0.311**	(0.139)
	$50,000 - $99,999	-0.298*	(0.160)	-0.516****	(0.101)
	$100,000 - $199,999	-0.211	(0.145)	-0.278****	(0.084)
	I'd rather not report	-0.198	(0.178)	-0.302***	(0.103)
	Years of living in home	0.008**	(0.004)	0.010****	(0.003)
	Pets outdoors (yes=1)	-0.087	(0.086)	-0.089	(0.058)
	Gender (male=1)	0.297****	(0.090)	0.044	(0.065)
	Age over 65 (yes=1)	0.241**	(0.112)	-0.003	(0.075)
	Have children (yes=1)	0.049	(0.095)	-0.021	(0.066)
	Highest degree of education (Baseline: Advanced degree)				
	No college	0.132	(0.113)	-0.022	(0.076)
	College degree	-0.043	(0.101)	-0.023	(0.066)
Property effect (Z_i)	Lot size (acre)	-0.530****	(0.087)	-0.131**	(0.057)
	House age (years)	-0.019****	(0.002)	-0.007****	(0.002)
	House size (1,000 square feet)	0.415****	(0.087)	0.109**	(0.049)
Informal neighborhood effect (M_i)	Difference in lot size	0.501****	(0.134)	0.064	(0.096)
	Difference in house age	0.011***	(0.003)	0.004	(0.003)
	Difference in house size	-0.180*	(0.105)	-0.018	(0.061)
Formal neighborhood effect (N_i)	HOA and NA affiliation (Baseline: Neither HOA nor NA)				
	HOA (yes=1)	0.590**	(0.280)	0.372***	(0.126)
	HOA with rules (yes=1)	-0.116	(0.322)	-0.265*	(0.137)
	NA (yes=1)	0.071	(0.103)	0.153**	(0.074)
	NA with rules (yes=1)	0.650***	(0.232)	0.090	(0.125)
	Constant	0.426	(0.303)	0.883****	(0.190)
	Log likelihood	-1,672		-2,213	
	Chi-square	304.2 (df. = 22)		140.6 (df. = 22)	
	Prob > Chi-square	0.000		0.000	
	Number of observations	2,635		1,372	

Standard errors in parentheses. **** p<0.001, *** p<0.01, ** p<0.05, * p<0.1.