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Spatial Aggregation Bias in Implicit Prices of Environmental Amenities

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Abstract

Applications of hedonic price functions aimed at eliciting implicit prices of environmental goods generally rely on spatially aggregated measures to proxy for micro-level perceptions of these amenities. This paper provides empirical evidence of the bias that arises in the elicitation of these implicit prices due to spatial aggregation. Cross-sectional data on more than 12,000 rental homes is used to derive implicit prices of air quality, using households' perceptions of air pollution aggregated at different spatial levels. Results show that higher aggregation levels add a downward bias to marginal willingness-to-pay measures for air quality improvements, increasing point estimates of the price of air quality. These findings suggest caution when interpreting implicit prices elicited from spatially aggregated measures of environmental amenities.

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1. Introduction

Common applications of hedonic price functions to the housing market relate the price of the house to a vector of its structural, neighborhood, and non-market amenities, with the purpose of capturing the price of these attributes hidden in the overall price of the house. This price function is an equilibrium outcome that emerges from interactions between buyers and sellers in this market. The use of hedonic price theory to elicit these implicit prices should, therefore, consider measures of housing attributes that consistently reflect what market participants perceive (Michael et al., 2000; Champ et al., 2003). While this is an easy task for most of the attributes, it is not so for non-market features widely known to affect housing prices such as environmental quality (Nelson, 1978; Kim et al., 2003). Hedonic studies all too often rely on aggregated indicators of environmental quality as a proxy for micro-level perceptions of these amenities, even though their focus is often on localized externalities for which individual-level information is crucial (Champ et al., 2003). This paper provides the first approximation aimed towards understanding how well aggregated measures approximate micro-level perceptions of environmental quality. Specifically, I study how implicit prices of environmental quality change with different aggregation levels of the environmental amenity.

The sensitivity of analytical results to the definition of the geographical units is not new to statistical analysis. The modifiable areal unit problem (MAUP), through its scale effect, summarizes the consequences that combining areal data into sets of increasingly larger areal units of analysis has on statistical results and inference (Yule, 1950; Openshaw and Taylor, 1979; Openshaw, 1984). This scale effect has been shown to distort the heterogeneity of spatial units in a wide variety of empirical applications ranging from economic geography (Briant et al., 2010), to health economics (Parenteau and Sawada, 2011; Lindo, 2015) and landscape ecology (Jelinski and Wu, 1996). In environmental economics, however, its impact is still scarce. Early work by Shultz and King (2001) approximates the consequences that the scale effect has on land-use data, documenting only minor changes in the implicit prices of an array of open-space amenities. This paper complements Shultz and King (2001)'s work by studying the effects of geo-aggregating the environmental amenity while maintaining the housing information at the household level, which allows me to isolate the scaling of the amenity as a separate event. In addition, I consider alternative spatial levels for the amenity variable that are as detailed as at the household level, a feature that is not addressed in Shultz and King (2001).

I particularly study how several spatial aggregation levels affect marginal willingness-to-pay (WTP) point estimates for air quality improvements. First, I present the theory of the scale effect on the WTP calculation. I show that the spatial aggregation of the air pollution disamenity introduces bias to marginal WTP measures, increasing the price of air quality.[1] I corroborate these findings with an empirical exercise that uses households' perceptions of the amenity as a benchmark model. From a policy perspective, these results suggest caution when deriving welfare effects from air quality deteriorations using point estimates elicited from aggregated measures of air pollution.

[1] This result is consistent with previous applications of the scale effect to health economics (Lindo, 2015) and education (Hanushek et al., 1996).

2. Spatial Aggregation Bias

Assume that the researcher is interested in the estimation of the following equation:

$$y_{ij} = \gamma_0 + \gamma_1 x_{ij} + \gamma_2 q_{ij} + \epsilon_{ij}, \tag{1}$$

where y_{ij} is the housing price (in logs) faced by household i located at a spatial unit j (with $i = 1, ..., I$ and $j = 1, ..., J$; and $J < I$); x_{ij} is a covariate varying across households and spatial locations; and ϵ_{ij} is an error component. The variable of interest in equation (1) is q_{ij}, which measures household i's perception of some specific environmental amenity. Suppose q_{ij} represents air pollution in the neighborhood where house i is located. The coefficient γ_2 is, therefore, the marginal WTP for air quality improvements, implicit in the overall price of house i.

Consider now that q_{ij} is unobservable to the researcher. Instead, he/she only observes q_j^*, which varies across spatial units but not within them. This paper borrows from Geronimus et al. (1996) to compare estimates in equation (1) using q_j^* as a proxy for q_{ij}. Let the relationship between q_{ij} and q_j^* be as follows:

$$q_{ij} = \beta q_j^* + \nu_{ij}. \tag{2}$$

The coefficient β in equation (2) will be equal to one whenever q_j^* represents the within-group mean of q_{ij}.[2] In this case, and under the standard assumptions of $E(\epsilon_{ij}) = E(\nu_{ij}) = 0$, $cov(x_{ij}, \epsilon_{ij}) = cov(q_{ij}, \epsilon_{ij}) = 0$, and $cov(q_{ij}^*, \nu_{ij}) = cov(q_j^*, \epsilon_{ij}) = 0$, Ordinary Least-Square (OLS) consistently estimates γ_1 and γ_2 in equation (1).

Inconsistency of OLS arises when $\beta \neq 1$, i.e. when the aggregated variable inadequately represents the i-level variable. Consider the situation of a monitoring station that is located upstream from a polluting facility, but whose readings are used by the researcher as a proxy for the air quality conditions that affect downstream households as well. In this case, the air quality relationship between upstream and downstream households will be systematically different in alternative units of aggregation (Hammond, 1973). In consequence, hedonic estimations using q_j^* will fail to account for heterogeneities in the air quality amenity within groups, underestimating air quality perceptions for downstream housing units. Formally, let the proximity of a house i to a polluting facility P be captured (along the unity) by x_{ij}. The regression of q_{ij} on both x_{ij} and q_j^* can be expressed as follows:

$$q_{ij} = x_{ij}\beta_1^{'} + \beta_2^{'} q_j^* + \nu_{ij}^{'}. \tag{3}$$

Under $cov(q_j^*, \nu_{ij}^{'}) = cov(x_{ij}, \nu_{ij}^{'}) = 0$, and perfect correlation between q_{ij} and q_j^*, $\beta_1^{'} = 0$, and thus, consistency of $\hat{\gamma}_1$ and $\hat{\gamma}_2$ holds. When $\beta_1^{'} \neq 0$, however, it is straightforward to show that γ_1 and γ_2 in equation (1) will be inconsistently estimated. Let y, q, and q* be $N \times 1$ vectors, x be a $N \times 2$ vector (includes the unity), and $\mathrm{M_x}$ be the complementary

[2] Equation (2) is a special case of the random coefficient model, or sometimes called, the random trend model (Wooldridge, 2010), where the random coefficient has been discomposed into their mean β and deviations μ_i, with the latter being captured in equation (2) by the within-group mean q_j^*. The consequences of omitting this additional source of heterogeneity, however, are outside the scope of the present study.

projection matrix of $\mathrm{x}(\mathrm{x}^{\mathrm{T}}\mathrm{x})^{-1}\mathrm{x}^{\mathrm{T}}$. Using the Frisch-Waugh-Lovell (FWL) theorem:

$$\hat{\gamma}_2 = (\mathrm{q}^{*\mathrm{T}}\mathrm{M}_{\mathrm{x}}\mathrm{q}^*)^{-1}(\mathrm{q}^{*\mathrm{T}}\mathrm{M}_{\mathrm{x}}\mathrm{y}), \tag{4}$$

and thus,

$$plim\ \hat{\gamma}_2 = \gamma_2 \beta_2^{'}. \tag{5}$$

Equation (5) shows the bias that affects the OLS estimator of γ_2, when the spatially aggregated variable is only imperfectly correlated with the i-level variable. A similar result can be shown for γ_1 (see Appendix for full derivations). The quantity $1 - \beta_2^{'}$ gives the proportional bias in $\hat{\gamma}_2$. As the relationship between q_{ij} and y_{ij} is expected to be negative whenever q_{ij} represents pollution, a downward bias means that the marginal WTP estimate for an improvement in the amenity will be higher in magnitude, and so its implicit price. The Appendix section shows how this bias could be exacerbated due to omitted variables.

3. Data

The data come from the 2015 National Socioeconomic Characteristics Survey (CASEN), a nationally-representative survey with information on more than 12,000 renting households in Chile. Households in this survey report information on their dwellings' structural characteristics, their rent and their neighborhoods' attributes, including their perceptions of air pollution. I merge this information with city-level attributes that come from the National System of Municipal Information (SINIM). I also consider crime rates extracted from the Crime Prevention Sub-Secretary (SPD). Summary statistics are displayed in Table I.

4. Empirical Strategy

4.1 Perceptions of Air Pollution

Households in CASEN report the frequency with which they observe air pollution in their neighborhoods using a four-point scale ranging from "never" to "always". I assign weights to each of these categories using ridit analysis, a non-parametric tool that allows comparison of more than two datasets with ordered qualitative data (Bross, 1958). I observe the distribution of households and construct a numerical quantity ("ridit"), which works as an index of air pollution perceptions. Formally, let $x_1, x_2, ..., x_n$ be the ordered perception categories, and p the probability function defined with respect to the reference category $p_i = Prob(x_i)$, with $i = 1, ..., n$. A ridit is calculated as follows:

$$Ridit_i = \begin{cases} 0.5p_i + \sum_{k<i} p_k & if \quad i > 1 \\ 0.5p_i & if \quad i = 1. \end{cases} \tag{6}$$

A low ridit value for category i is interpreted as only a few households choosing a category k such that $k < i$. After obtaining ridits for each household, I follow the local geographical hierarchical structure to aggregate them at both the neighborhood and the county level.

Table I: Descriptive Statistics of Covariates

Variables	Mean	Sd	N	Source
Panel A. Dwelling Charateristics (household level)				
# of Bedrooms	2.413	0.933	12,913	CASEN
# of Bathrooms	1.193	0.486	12,913	CASEN
Dwelling Type (Base = Precarious)			12,913	CASEN
Proportion Row Units	0.427	-		
Proportion Regular Units	0.343	-		
Proportion Apartments w/Elevator	0.077	-		
Proportion Apartments wo/Elevator	0.135	-		
Walls Material (Base = Precarious)			12,913	CASEN
Proportion Reinforced Concrete	0.188	-		
Proportion Masonry	0.470	-		
Proportion Drywall	0.311	-		
Floors Material (Base = Precarious)			12,913	CASEN
Proportion Wood	0.366	-		
Proportion Tile	0.485	-		
Proportion Carpet	0.050	-		
Proportion Cement	0.050	-		
Roofs Material (Base = Precarious)			12,913	CASEN
Proportion Roof Tiles	0.096	-		
Proportion Concrete	0.171	-		
Proportion Sheet Metal/Zincstrips	0.732	-		
Proportion Clinkstone	0.000	-		
Dimension (Base = Less than 30m2)			12,913	CASEN
Proportion 30-40m2	0.200	-		
Proportion 41-60m2	0.398	-		
Proportion 61-100m2	0.261	-		
Proportion 101-150m2	0.055	-		
Proportion +150m2	0.015	-		
Urban (%)	0.936	-	12,913	CASEN
Panel B. Neighborhood Attributes (household level)				
Proportion Sport Center < 2.5km	0.916	-	12,808	CASEN
Proportion Green Areas < 2.5km	0.927	-	12,862	CASEN
Proportion School < 2.5km	0.959	-	12,860	CASEN
Panel C. City Attributes (city level)				
Population	101,549	133,001	315	SINIM
Crime (per 1,000 inab.)	2,503	1,856	320	SPD
Poverty (%)	0.21	0.11	320	SINIM
Waste Disposal (%)	0.23	0.16	316	SINIM

Notes: The crime variable considers criminal offenses of strong social connotation. p.c. = *per capita*.

Table II contains the descriptive statistics of the air pollution perceptions at each of these spatial levels.

Table II: Descriptive Statistics for Air Pollution at Different Spatial Levels

Variable	Mean	S.D.	Min	Max
Household	0.502	0.253	0.304	0.958
Neighborhood	0.500	0.138	0.304	0.958
County	0.500	0.093	0.304	0.926

4.2 Hedonic Price Estimation

I elicit implicit prices for air quality from the following hedonic price estimation equation:

$$y_{hnc} = \alpha + \mathbf{H}_{hnc}\delta + \beta^s A_s + \phi + \epsilon_{hnc}, \tag{7}$$

where y_{hnc} is the rental price (in natural logs) of house h in neighborhood n in county c; $\mathbf{H}$ is a vector of attributes; ϕ is a set of dummies at a specific spatial level (i.e. region) intended to mitigate some of the omitted variable bias that affects hedonic estimations (Kuminoff et al., 2010); and ϵ_{hnc} is an error term. Perceptions of air pollution in equation (7) are captured with A_s, where s represents different levels of spatial aggregation, i.e. $s = \{h, n, c\}$. The key parameter in equation (7) is β^s that indicates the average marginal WTP for air quality improvements at a specific aggregation level s. Since micro-level data can better discriminate between alternative specification models (Arbia and Petrarca, 2011), I use household-level data as the benchmark model. Consistent with a downward bias derived in Section 2, β^s is expected to decrease relative to the benchmark with higher aggregation levels. Equation (7) is estimated using an OLS estimator.

5. Spatial Aggregation Bias in Implicit Prices for Air Quality

Columns (1)-(3) in Table III summarize the point estimates of the marginal WTP for air quality improvements estimated from equation (7) for alternative aggregation levels (i.e. household, neighborhood, county) for the air pollution variable. Columns (4)-(6) display the results for an alternative log-log specification of equation (7). Findings in column (1) for the benchmark model show that, on average, households are willing to pay 7% per unit-increase in the air quality index. Point estimates decrease by 6 percentage points (column 2) and by 10 percentage points (column 3) when this index is aggregated at the neighborhood level and at the county level, respectively. Results from a chi-square test reject the null of equal point estimates between the micro-level variable and the aggregated variables at the 5% in the first case (households vs. neighborhoods, $\chi^2 = 4.09$, $p - value = 0.043$), and at the 10% in the second case (households vs. counties, $\chi^2 = 3.09$, $p - value = 0.079$). These results formally reflect the bias affecting point estimates of marginal WTP measures for air quality. Similar results are found when using a log-log specification in columns (4)-(6), which rejects the possibility of observing these results due to a misspecification of the functional form.

Figure 2 depicts the point estimates and the 95% confidence intervals (CI), of the marginal

Table III: Marginal Willingness-to-Pay Estimates for Air Quality Improvements

	Semi-log Functional Form			Log-log Functional Form		
	Household	Neighborhood	County	Household	Neighborhood	County
	(1)	(2)	(3)	(4)	(5)	(6)
Air pollution	-0.073***	-0.128**	-0.165**			
	(0.018)	(0.051)	(0.061)			
log(Air pollution)				-0.037**	-0.053*	-0.070**
				(0.009)	(0.026)	(0.029)
Obs.	12,619	12,620	12,620	12,619	12,620	12,620
R^2	0.46	0.46	0.46	0.46	0.46	0.46

Notes: All regressions include structural characteristics, dummy variables for proximity to a sport center, to a park, and to a school, an indicator for urban/rural area, city-poverty and -crime rates, population level (in logs), municipal per capita expenditures in waste removal and region fixed effects, as controls. Clustered standard errors by region in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$

WTP measures for air quality improvements, while Figure 1 exhibits the estimated implicit prices from the semi-log specification. Point estimates of the marginal WTP measures in Figure 1 move to the left with higher aggregation levels, exhibiting larger CI due to the higher standard errors from the aggregation. As shown by Figure 1, this translates into higher implicit prices of the amenity. Mainly, the estimated implicit price of air quality is 76% higher at the first aggregation level relative to the benchmark (significant at the 5%), and 125% higher at the second aggregation level (significant at the 10%). Results for a likelihood-ratio test on nested models formally indicate that both aggregated models are nested within the benchmark model that considers the amenity variable at the micro-level ($p - value = 0.000$).

6. Robustness Check

The study of air quality, as opposed to other amenities, offers the unique opportunity to explore the role of spatial spillovers when eliciting implicit prices of environmental amenities.[3] The heterogeneous dispersion of air pollutants across space dictates that households' exposure to air pollution is not uniquely driven by emissions occurring in their neighborhoods but also by the spread of pollutants released in nearby areas. In this case, changes in air pollution perceptions in cross-sectional neighboring units are expected to be capitalized into housing prices of other units, adding an indirect or spillover effect to the implicit price of air quality. To empirically assess this spatial dependence at different aggregation levels of the amenity, I estimate a spatial model that considers an exogenous interaction effect of the air quality variable among spatial units. These spatial lags are captured by the interaction between the air quality variable, A_s, and a matrix $\mathbf{W}$ of spatial neighbors. I specify this Spatial Lag of X (SLX) model (Anselin, 2003) as follows:

[3] I enormously thank an anonymous referee for this suggestion.

Figure 1: Point Estimates and 95% CI of Implicit Prices of Air Quality

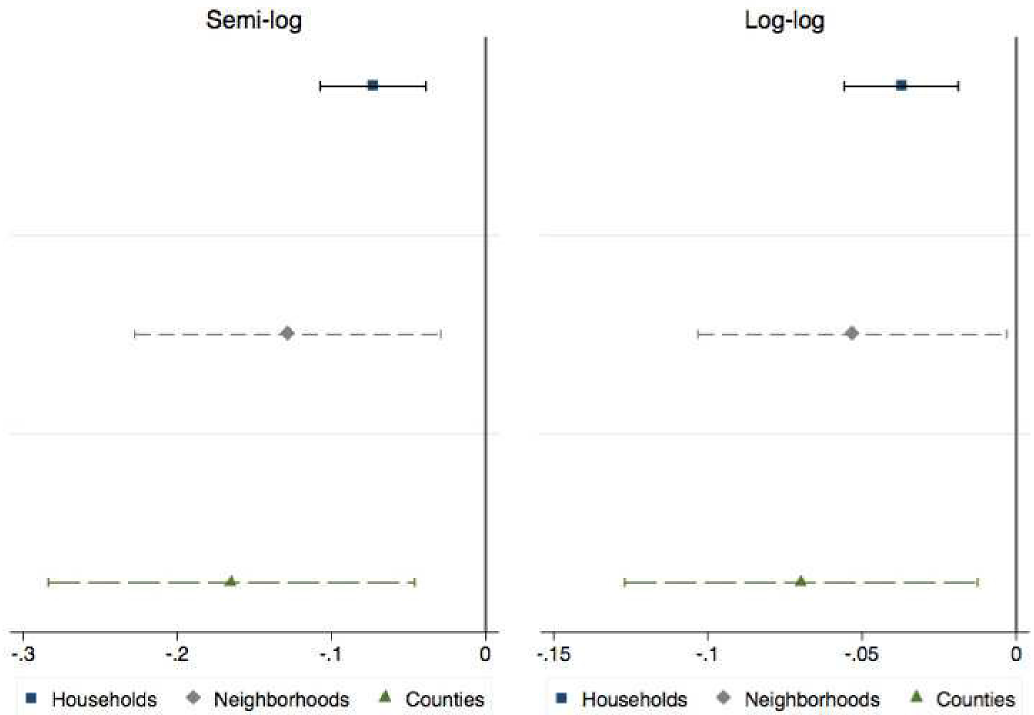
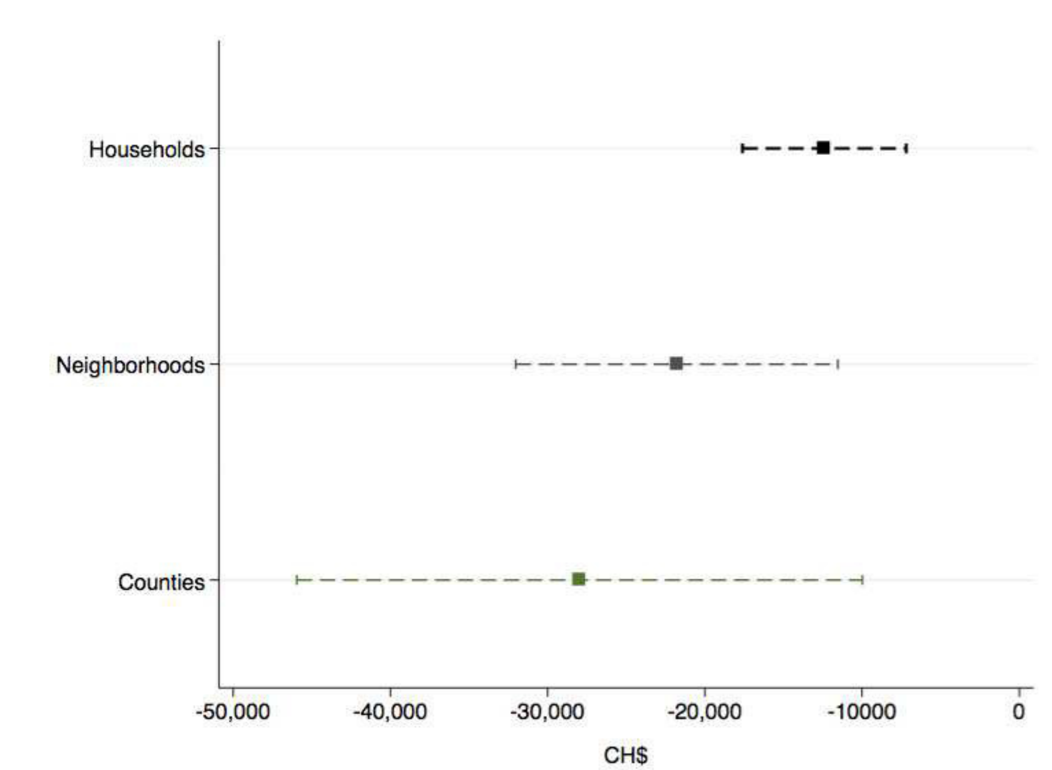


Figure 2: Point Estimates and 95% CI of Marginal WTP for Air Quality Improvement



$$y_{hnc} = \alpha + \mathbf{H}_{hnc}\delta + \beta^s A_s + \mathbf{W}_{hnc} A_s \theta^s + \phi + \epsilon_{hnc}, \tag{8}$$

where $\mathbf{W}_{hnc}$ is the spatial weights matrix identifying the spatial interdependence of units at the household h, neighborhood n, or county level c. The elicitation of the implicit price of air quality from equation (8) involves the derivation of a direct effect, β^s, at different spatial levels, and an indirect (spillover) effect, θ^s, which reflects the influence of the air quality conditions in neighboring cross-sectional units.

Unfortunately, the lack of data on the geographical location of rental properties and neighborhoods prevents the calculation of geo distance-based spatial weights matrices for the first two aggregation levels, h and n. As a solution, I define $\mathbf{W}$ to be a first-order contiguity matrix whenever s captures ones of these two levels. Entries for $\mathbf{W}$, therefore, take the value of 1 for houses (neighborhoods) located in the same neighborhood (county), and 0 otherwise. This also precludes the use of the benchmark model defined at the household level, as the first spatial tier defining dependence occurs now at the neighborhood level. This implies that the aggregation of the amenity variable, in this exercise, is only feasible at the neighborhood and at the county level. For a spatial dependence at the county level, I calculate the $\mathbf{W}$ matrix using the inverse of the geographical distance between the center of any two counties. Table IV displays the results for the SLX model.

Consistent with the results in Table III, the point estimates of the direct effect in Table IV increase in magnitude with the different aggregation levels of the air pollution amenity, particularly for the semi-log specification in column (1). Regarding the magnitude and significance of the indirect (spillover) effects, however, findings in column (2) and (4) show ambiguous results. For the semi-log specification, results in column (2) indicate that rental prices are negatively correlated with air pollution levels in contiguous neighborhoods (panel A), which could be capturing a situation with neighborhoods small in magnitude and close in proximity such that their air quality conditions are similar across them. Moreover, contiguous neighborhoods are in most cases part of the same county and, therefore, subject to similar institutional settings that make the idea of homogeneous air quality across them even more feasible. Yet, when the spatial dependence is defined at a higher aerial level (panel B), the estimated indirect effect in column (2) suggests that rental prices are positively affected by air pollution levels in nearby counties. The intuition behind a negative direct effect and a positive spillover effect is consistent with households avoiding areas with poor air quality and, instead, locating themselves in places with less airborne contamination, which pushes rental prices up in proximate but more pleasant counties that due to their larger size are less likely to perceive air pollution spillovers. Notwithstanding, the existence of omitted variables occurring at the same aerial level as the one defining the contiguity (e.g. counties), could add an upward bias to the spillover estimates in panel B (Hanushek et al., 1996) helping as well to explain the change in sign between the disaggregated model in panel A and the aggregated in panel B. Consistent with previous research (Chung and Hewings, 2015) however, the estimated spillover effects in columns (2) and (4) of Table IV all decrease in magnitude with higher aggregation levels. In addition, they are all found to be small in magnitude, and in some cases not statistically different from zero. The ambiguity of these results could be explained by the two sources of heterogeneity that now change simultaneously (Arbia and Petrarca, 2011), that is, the aggregation level of the amenity variable as well as the

Table IV: Marginal Willingness-to-Pay Estimates in a SLX Model

	Semi-log Functional Form		Log-log Functional Form	
	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect
	(1)	(2)	(3)	(4)
Panel A. First-Order Contiguity Defined by Neighborhoods				
Amenity Variable at the Neighborhood Level	-0.080*	-0.007**	-0.068**	0.003
	(0.049)	(0.003)	(0.028)	(0.002)
Obs.	12,620		12,620	
Likelihood Ratio Test (χ^2)	13.15		3.87	
$p-value$	0.000		0.049	
Panel B. First-Order Contiguity Defined by Counties				
Amenity Variable at the Neighborhood Level	-0.145**	0.0008***	-0.040	-0.0006**
	(0.052)	(0.0001)	(0.028)	(0.0002)
Obs.	12,620		12,620	
Likelihood Ratio Test (χ^2)	60.5		48.68	
$p-value$	0.000		0.000	
Panel C. Inverse Geo-Distance Across Counties				
Amenity Variable at the County Level	-0.177**	-0.00001	-0.078**	0.00006
	(0.060)	(0.0002)	(0.029)	(0.0002)
Obs.	12,580		12,580	
Likelihood Ratio Test (χ^2)	27.57		0.61	
$p-value$	0.000		0.436	

Notes: All regressions include structural characteristics, dummy variables for proximity to a sport center, to a park, and to a school, an indicator for urban/rural area, city-poverty and -crime rates, population level (in logs), municipal per capita expenditures in waste removal, and region fixed effects, as controls. Clustered standard errors by region in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$

contiguity matrix, which prevents more straightforward conclusions regarding the expected sign of the indirect effect on the implicit price of air quality. In any case, likelihood ratio tests on the goodness of fit of the SLX models relative to the OLS specifications reveal that in most cases the former outperforms the latter. This situation highlights the need for more research regarding the impact of the scale effect on hedonic estimations that consider spatial dependence of their cross-sectional units.

7. Concluding Remarks

This paper studies how the spatial aggregation of environmental amenities can threaten the unbiasedness of implicit prices in hedonic price applications. Simple comparisons across point estimates of the price of air quality at alternative aggregation levels show that the use of spatially-aggregated measures on environmental amenities might substantially affect the magnitude of their estimated price. This note suggests future researchers should consider the potential role of aggregation bias when using proxies for environmental amenities and recommends that policy makers exercise some caution when interpreting past estimates on implicit prices of environmental quality elicited from aggregated measures of this amenity.

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