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Capitalization as a Two-Part Tariff: The Equilibrium Structure of Housing Prices*

H. Spencer Banzhaf† Kyle Mangum‡

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Abstract: Standard hedonic housing price regressions may be mis-specified. They impose that neighborhood amenities affect prices proportionately. In contrast, we suggest that amenities may be capitalized via a two-part tariff: an extensive margin "ticket" to enter a community and an intensive margin price per unit of housing services. A theoretical model shows that extensive margin pricing will emerge when there are binding restrictions on the number of housing units. Using data on housing transactions across U.S. urban markets, we show that two-part pricing is ubiquitous and especially pronounced in markets with high land use regulation and/or an older housing stock. Moreover, two-part pricing is economically relevant: Ignoring it generally understates the willingness to pay of poorer households. We illustrate this pattern with an application to school quality, using a boundary discontinuity design in a two-part pricing framework. We provide user-friendly MATLAB and R code for estimating the generalized model.

Keywords: capitalization, amenities and public goods, two-part pricing, hedonics, housing markets, land-use regulation, school quality

JEL Codes: R31, R52, H41, H73, D45

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1 Introduction

Tiebout (1956) famously argued that there is a market-like process for allocating local public goods, with local jurisdictions supplying them to attract residents who "vote with their feet" to find jurisdictions with a desirable mix of amenities. But this market analogy raises the question of just what serves as a price of amenities. Tiebout's simple model assumed that it was non-distortionary head taxes. As with other markets, the head tax coordinates the distribution of amenities: Households sort into communities based on their differing demands, with high-demand households paying a higher tax and receiving more amenities. But households still must purchase housing, so there is a two-part tariff: at the extensive margin, they must purchase a "ticket" to enter the community and receive its benefits, then they must purchase land and housing, with bigger houses costing more.

Of course, in the real world, jurisdictions typically use *ad valorem* property taxes. This fact seemingly implies that there is only a single gross-of-tax price of housing, with no two-part tariff. Accordingly, most empirical Tiebout models have ignored the role of tickets. For example, hedonic price regressions typically use a semilog functional form that restricts amenities to have a constant proportionate effect on housing values (e.g., Avenancio-León & Howard, 2022; Banzhaf, 2021; Bishop et al., 2020). Structural models of locational choice also typically impose this assumption (Kuminoff, Smith, & Timmins, 2013). Consequently, amenities are priced into per-unit housing services, without any tickets. This departure from Tiebout's idealized model potentially gives rise to a "jurisdictional choice externality," in which households seeking high amenities can free ride on neighbors by buying smaller houses, causing overcrowding (Calabrese, Epple, & Romano, 2011).

Hamilton (1975; 1976) extended Tiebout's model to account for just such issues (see also Fischel 2001 for discussion and Brueckner 2023 for a re-evaluation). Hamilton suggested that zoning and other land-use restrictions can prevent such distortions by restricting access to a community, preventing over-crowding. The restrictions create a shadow price that induce a two-part tariff. Glaeser and Gyourko (2003), Glaeser, Gyourko, and Saks (2005), Gyourko and Krimmel (2021), and Turner, Haughwout, and Van Der Klaauw (2014) have confirmed empirically that building restrictions do increase housing prices, especially via tickets (see also Glaeser and Gyourko 2018 for a review). However, they do not consider how this mechanism affects the capitalization of amenities in prices across communities and, hence, how it drives the sorting process that allocates amenities to households.

Using a simple theoretical sorting model, we show how land restrictions affect the equilibrium structure of housing prices in ways that have not previously been considered. We clarify how and when they create tickets and show that they can fundamentally change the way amenities are capitalized into local housing values. In summary, the presence of binding restrictions means amenities can be capitalized into tickets as well as into unit prices for land or housing services.

To test our theory, we compile a dataset of over 140 metro areas in the United States, with observed transaction prices and property attributes, placed into over 23,000 neighborhoods defined by elementary school attendance zones. We estimate non-linear pricing functions for these neighborhoods which nest the standard semilog model, generalizing them to allow for tickets. Additionally, we use data on local amenities, including school test scores, air quality, hazardous waste sites and distance to the central business district (CBD), and estimate the extent to which they are priced into tickets or the price per unit of housing services.

We find that, in the majority of housing units, amenities are capitalized more into ticket prices than per-unit prices of housing services. In an average U.S. market, moving a median-sized property from a neighborhood at the 25th percentile of amenities to the 75th percentile increases the price of the home by $40,200, of which $31,100, or 77 percent, is due to the higher ticket price in the premium neighborhood. Moreover, in line with our theory, capitalization into tickets is greater in markets with more stringent zoning regulations. For a more heavily regulated market, the ticket associated with the premium neighborhood increases 36 percent, to $42,200. This general result is robust to alternative specifications of housing services, and to alternatives in measure of land-use restrictions and their geographic scales.

Our theoretical model focuses on regulation as one particular channel through which tickets arise, one salient in the literature. But there may be myriad reasons. For example, the durability of housing may create some path dependence that locks in a historical configuration. We test for this pattern and find it too holds. Additionally, fixed costs of constructing a housing unit (say, the cost of a construction crew showing up) may also generate tickets. Hence, one is left to expect that tickets will frequently show up in the housing market.

Our findings have at least three implications for our understanding of housing markets and capitalization. First, they clarify the effects of land-use restrictions—specifically how their equilibrium effects on prices vary by small and large housing units, low- and high-amenity areas, and the interaction of the two. Second, they suggest that many standard hedonic models are mis-specified. The standard semilog specification imposes the restriction that a change in amenities affects prices proportionately, which will be incorrect if there is capitalization into tickets. Similar problems plague any structural model of locational choice that ignores community-level tickets.

Third, our findings have important distributional implications. Common methods that force proportionate effects mechanically imply that buyers of large properties (typically, the rich) have higher willingness to pay (WTP) for amenities. In contrast, capitalization into tickets implies a constant premium for amenities paid by all households. Thus, the existence of tickets implies both that the poor are paying more for amenities than standard models predict and that, therefore, by revealed preference, they are willing to do so.

Finally, we illustrate these insights with an application to public schools. We estimate border-discontinuity models (Bayer, Ferreira, & McMillan, 2007; Black, 1999) to recover the implicit price of school quality as measured by achievement. We estimate these models separately for each metro area, identifying school effects from quasi-experimental discrete variation at the border of each elementary school attendance zone (which are nested inside political units), a border around which other amenities and land regulations are approximately constant. We compare the standard semilog model to our generalized model allowing for tickets–the two-part tariff–using both linear and nonlinear approaches. We find a pattern in line with our theory. The two-part tariff models indicate that for many cities, the school premium is only slightly increasing in the size of the home, whereas the semilog models imply a steep gradient of the premium with respect to property size. We also show that, consequently, the semilog model ascribes a lower value to school quality for occupants of smaller homes. Thus, we show that ignoring tickets has substantial implications for findings about distributional disparities. We provide user-friendly MATLAB and R code for our generalized model, which can be used in future applications.

The paper proceeds as follows. Section 2 presents a theoretical model of housing markets, hypothesizing when a two-part tariff emerges in equilibrium and how it affects capitalization of amenities. Section 3 describes the data and Section 4 our empirical strategy to recover generalized pricing functions. Section 5 tests for the existence of two-part pricing. Section 6 discusses approaches for incorporating two-part tariffs into hedonic models, and Section 7 demonstrates with the empirical application to public school quality. Section 8 concludes.

2 Theoretical Framework

We begin with an intuitive discussion of the emergence of tickets in the presence of land use constraints. Adding additional structure, we then formally prove existence of a two-part pricing equilibrium under such constraints. Finally, we provide sufficient conditions for capitalization of amenities into tickets.

2.1 The Role of Tickets

Consider a world with one city and an outside option. The outside option has a perfectly elastic supply of land available at a given price per unit area, β^O. In contrast, the city has an endogenously determined set of lots available for purchase. Additionally, it is differentiated by an exogenously determined amenity G (normalized to zero in the outside option).

On the demand side, a set of heterogeneous households $1...i...I$ have utility $u_i(k, h, G)$ which is increasing in numeraire consumption k, land consumption h, and G. Households choose whether to locate in the city and, if so, the lot ℓ that maximizes their utility, given a (possibly non-linear) price function, $p_\ell = p(h_\ell)$. Given the utility function, the pricing function is continuous and increasing in h, with $p(h) > \beta^O h$ for all values of h. We assume for exposition that the price function also is differentiable, but this is not necessary.

On the supply side of the market, we begin with the case where the city has no land use restrictions, so its land can be carved into any arbitrary set of lots. Price-taking developers serve as arbitrageurs who can subdivide lots, assemble them, or buy land from some and add it to others. An equilibrium price function must equalize the *marginal value* of land at each lot within the city, otherwise developers would arbitrage the difference by reallocating land from a lot where its marginal value is lower to one where it is higher. Likewise, this marginal value must be equal to the *average* value of a lot (i.e., dollars per square foot). Otherwise, if the marginal value were higher than the average value, developers would profit by assembling land into fewer, larger lots. Alternatively, if the marginal value were lower, developers would subdivide lots to create more, smaller lots. Thus, without land-use restrictions, the following two equilibrium conditions must hold:

$$\frac{\partial p}{\partial h}|h_\ell = \beta \text{ for all } \ell \tag{1}$$

$$\frac{\partial p}{\partial h}|h_\ell = \frac{p_\ell}{h_\ell} \text{ for all } \ell \tag{2}$$

for some constant $\beta > 0$. The first condition is the equimarginal principle operating on the intensive margin. The second is like the free-entry condition at the extensive margin.

Integrating Equation (1) gives

$$p_\ell = \alpha + \beta h_\ell, \tag{3}$$

for some constant of integration α. Dividing by square footage gives $p_\ell/h_\ell = \alpha/h_\ell + \beta$. Equation (2) then requires α=0. Consequently, $p(h_\ell) = \beta h_\ell$. That is, because of the no-arbitrage condition at the extensive margin, there are no tickets in the community. Furthermore, with $\beta > \beta^O$, amenities are capitalized into the per-unit price of land or housing. This model represents the consensus view of hedonic pricing.

We now relax the assumption of full malleability, restricting the number of lots to be less than L. There are now two equilibrium conditions to meet, market clearing in the number of lots as well as in total land. One price alone cannot meet both conditions. The unconstrained equilibrium with $p(h_\ell) = \beta h_\ell$ may result in "too many" small lots. Thus, the constraint introduces a shadow price on lots *per se*. Conditional on the number of lots, equilibrium condition (1) still is satisfied, i.e., $\partial p/\partial h_\ell = \beta$, otherwise developers could increase their profits by redistributing land (without changing the number of lots). Thus, Condition (3) also is satisfied, so $p_\ell = \alpha + \beta h_\ell$ for some constant of integration α. However, equilibrium condition (2), marginal versus average price, is no longer satisfied. Instead, $\partial p/\partial h_\ell < p_\ell/h_\ell$. The marginal value of land at the intensive margin is lower than its value at the extensive margin, so developers would like to subdivide land to create more, smaller lots, but they are restricted from doing so. Consequently, the average value is shrinking in lot size, which requires a constant term $\alpha_n > 0$ in the price function, or ticket (Glaeser and Gyourko 2003; Glaeser et al. 2005; Gyourko and Krimmel 2021).

The ticket is the shadow value of the constraint on the number of lots (or housing units). This constraint on lots is critical for the emergence of tickets. It may arise from zoning or from other frictions preventing new lots, such as historical lock-in.[1] The centrality of the restrictions on number of lots may be surprising, as Hamilton (1975) and Brueckner (1981, 2023) show tickets also emerge under a constraint on minimum lot size. However, in those models, the constraint is binding on everybody in a homogeneous community, so minimum lot sizes are equivalent to a restriction on the number of lots, as there is no land free to be reallocated to a new lot. On the other hand, Hamilton (1976) and subsequent discussion

[1]Demand-side frictions in household mobility can also affect hedonic equilibria (see, e.g., Kuminoff et al., 2013) but are outside the scope of this paper.

seem to imply that the restriction on lots causes tickets because of fiscal transfers from households in large lots to those in small ones, but our model with exogenous G indicates such transfers are not an essential part of the mechanism. (See Banzhaf & Mangum, 2019, for additional discussion.)

2.2 Existence of a Two-Part Pricing equilibrium

In this section we establish sufficient conditions for existence of an equilibrium with a two-part tariff, taking a partial equilibrium approach were rents are paid to absentee landlords. We also generalize the model to account for the production of housing through land and capital. To accomplish this, we make the following four assumptions.

1. The outside option has perfectly elastic housing available at price β^O, with no constraints. The city has an exogenous amenity G. Additionally, it has a continuously increasing housing supply function $h^s(\beta)$, which is bounded and has $h^s(0) = 0$. (Note the ticket α is pure rent which does not show up in housing supply.) The city has a maximum allowable measure of housing units, L.

2. There is Lebesgue-measurable continuum of households $i \in \mathcal{I}$, with continuous density over parameters governing housing demand, tastes for G, and income y_i, which is continuously distributed on the interval $(0, \bar{y}]$.

3. For each individual i, indirect utility conditional on residential location is a continuous function of income y_i, housing cost parameters α and β, and G, $V^i(y_i - \alpha, \beta, G)$. It has bounded derivatives $V^i_y = -V^i_\alpha > 0, V^i_\beta < 0$, and $V^i_G > 0$, resulting in finite WTP for G. Moreover $V^i_\beta < 0$ reaches its bound more slowly that V^i_G, in the sense that, for any G, there is sufficiently high β to make i prefer the outside option.

4. Conditional housing demand is given by Roy's identity: $h^{D,i}(y^i - \alpha, \beta) = -\frac{V^i_\beta}{V^i_y}$. It may be heterogeneous, but $\forall\, i$ it is differentiable, strictly positive at all $y - \alpha > 0$, bounded from above, and with bounded first derivatives $h^D_y > 0$ and $h^D_\beta < 0$.

Households live in the city if $V^i(y-\alpha,\beta,G) > V^i_O$. Denote the subset of households doing by $\mathcal{C}(\alpha,\beta,G) \subseteq \mathcal{I}$ with measure $\mu(\mathcal{C})$. Note that the constraint on housing can thus be written $\mu(\mathcal{C}) \leq L$. Then the two equilibrium conditions can be written:

$$\int_{i\in\mathcal{C}(\alpha,\beta,G)} h^{D,i}(y-\alpha,\beta,G)di = h^s(\beta), \tag{4}$$

$$\int_{i\in\mathcal{C}(\alpha,\beta,G)} di \leq L. \tag{5}$$

The first condition is the usual market clearing condition: the sum of housing demands in the city must equal supply. The second is the land use constraint: the measure of households sorting into the city (and occupying housing units) must be less than or equal to L.

We present the following theorem.

Theorem 1. Under Assumptions 1-4, there is an equilibrium $\beta > 0, \alpha \geq 0$ satisfying Conditions 4 and 5.

Proof. See Appendix A.1.

2.3 Capitalization of Amenities into Tickets

Because they represent the value of the right to enter a community, these tickets are likely to be greater in communities with higher amenities, thus providing another channel for capitalization. To see this intuitively, imagine an increase in G. Unless housing demand is strongly complementary to G, there would not be a large increase in housing demand from current residents of the city. But with higher G and no increase in housing prices, we would expect more people to want to enter. This will increase the ticket price to meet condition 5. We can prove this logic always holds under the following additional assumptions:

2′ The continuum of households $\mathcal{I}$ is described by the distribution of a single parameter with continuous density $f(\,)$ and bounded support. We focus on two possibilities: heterogeneity only in y, continuously distributed $f(y), y \in (0,\bar{y}]$, *or* homogeneity in y and heterogeneity in a taste parameter for G, $\phi \in [\underline{\phi},\bar{\phi}], \underline{\phi} > 0$ with continuous density $f(\phi)$.

5. V^i satisfies the single crossing property, such that the slope of an "indirect indifference

curve" in β-G space is increasing in either y or ϕ, corresponding to the cases of the previous assumption. That is, $\frac{\partial(-V_G/V_p)}{\partial y} > 0$ or $\frac{\partial(-V_G/V_p)}{\partial \phi} > 0$. This assumption ensures that there is a $\tilde{y}(\alpha, \beta, G)$ such that all households with $y_i \geq \tilde{y}$ prefer the city to the outside option, or, respectively, that there is such a $\tilde{\phi}$. (See, e.g., Calabrese et al., 2011.)

6. Housing demand is independent of G.

These assumptions induce sorting on a single dimension, yielding the following theorem.

Theorem 2. Under Assumptions 1, $2'$, and 3-6, α is non-decreasing in G and strictly increasing whenever the land use constraint is binding.

Proof. See Appendix A.2. A simple economic intuition underlies the formal proof. Because the land use constraint is binding, the same measure of households lives in the city at both levels of G. Furthermore, because they sort along a line, the same set of households do so. If α did *not* increase with G, then β would have to increase to maintain the land use constraint. But with the same households, the increase in β would result in excess supply of housing. Thus, the new equilibrium must involve an increase in α.

The proof relies on sorting on a single dimension. In more general cases, α might not be increasing in G if there is a second-order feedback effect, as follows. (i) As $\{\alpha, \beta, G\}$ change, even though the total population in the city remains constant, there is a resorting of household types; (ii) On average, the new residents have higher housing demand; (iii) Therefore, to maintain equilibrium in the housing market, β increases; and (iv) This increase in β is sufficient to maintain the land use constraint at a lower α. Nevertheless, as established earlier, some $\alpha > 0$ will be required. In Appendix A.3 we derive a specific condition for how big these second-order effects must be to offset the direct effects. We conjecture that, even in the more general case, the first-order effect captured by Theorem 2 will tend to dominate these second-order effects, resulting in capitalization of G into tickets.

In simulations we find this to be the case when households have Stone-Geary utility. This utility function, used in recent studies of sorting (e.g., Gaubert & Robert-Nicoud, 2025), does not impose the single crossing condition required by the proof, yet capitalization into tickets still occurs. It also nests other common functional forms, such as Cobb-Douglas. See Appendix A.4 for details. Figures A3 and A4 summarize the results of the simulations and illustrate the main themes of the paper. They show that tickets emerge only with land use constraints, and moreover that they are increasing in G.

In summary, we have established that tickets must exist when there are supply restrictions on housing units. This fact alone is justification to include tickets in empirical work, to avoid mis-specified models. Moreover, although we cannot guarantee that tickets will be increasing in amenities in all cases, there are powerful economic forces suggesting they usually will.

3 Data

This section summarizes the data we use to test for the emergence of tickets and capitalization of amenities into them.

3.1 Housing Data

Property Information and Transaction Prices. The main source of data is a national register of home sales paired with property characteristics, obtained from CoreLogic (which has since been renamed Cotality).[2] The data are drawn from public records of deed transactions and property tax assessments, the former containing sales prices and the latter containing attributes including location and property characteristics such as lot size, living area, units in structure, year built, and counts of rooms. The data also include detailed spatial information, which allows us to place the properties into 141 housing markets defined by core-based statistical areas (CBSAs), and then 23,707 neighborhoods within these markets.[3]

We use property transactions from 2005-2012, with all prices in our models converted to 2010 levels using the metro area price index from the Federal Housing Finance Agency.

[2]The data are made available under a license to the Federal Reserve System. Because these derive from public records, the same or similar data is available to other researchers through a variety of sources.

[3]We break the three largest metro areas into sub-markets: New York into its NY state and NJ components, Los Angeles into Los Angeles and Orange counties, and Chicago into Cook County and surrounding suburbs.

This time frame is driven by the availability of school attendance and performance data, described below. Additionally, we focus our analysis on single family homes, which are the most common structure type in the U.S. and are more likely to be owner-occupied. More importantly, they have a clear measure of land area associated with the structure.[4]

We further process the data to remove non arms-length sales and properties missing key attributes. In some cases, the property attribute is missing for all properties in the county; for example, if the county tax assessor does not collect the number of bathrooms. In that case, we maintain the properties in the sample, but the missing data may cause the market to be dropped from a model that requires the information for a measure of housing services. Hence, not every market will be in every model. To trim outliers, we drop transactions with prices below $10,000 or above $5 million, lots below 500 square feet or above 5 acres, and properties below 500 or above 10,000 square feet of living area.

Our final sample has 17.3 million transactions. Summary statistics and additional details can be found in Appendix B. Table B1 displays the cities in our sample, the number of unique properties for each city, the number of transactions (including repeat sales), average price, and number of neighborhoods (elementary school attendance zones).

3.2 Local Amenity Data

We assemble data on local amenity offerings from several sources.

Public Schools: Location. We define neighborhoods by their assigned public schools, as of fourth grade. We choose this definition for two reasons. The first is the importance of school quality to many households. The second is that school quality varies discretely at well-defined boundaries, whereas other attributes vary more continuously through space. Indeed, this fact is the basis of boundary discontinuity research designs in the empirical literature on WTP for school quality (Bayer et al., 2007; Black, 1999; Zheng, 2022).

[4] Specifically, we exclude any property that reports more than two units or fails to report lot size. This rule admits duplexes or homes with basement apartments, in-law suites, and the like. We control for the number of units in all property level regressions.

We assign properties to attendance zones using two methods. The first uses boundary attendance zones maps from the School Attendance Boundary Information Network System (SABINS) together with properties' latitude/longitude coordinates. These data are most complete for the 2009-2010 school year, which drives our time frame.

Although it is extensive, the geographic coverage of SABINS is not comprehensive, with some cities having incomplete maps. For the remaining properties, we use a two-step procedure. First, we place the properties into school districts using maps from the US Census Bureau. Next, we use school address data from the National Center for Education Statistics (NCES) to map each property to its closest elementary school within the boundaries of its district. Appendix Table B1 reports how many properties are matched to schools using attendance boundary files versus the district and nearest-school method. For our spatial discontinuity design (Section 7.2), we use only the former.

Public Schools: Quality. We use test score proficiency reports from the NCES as a measure of school quality. The NCES reports the percent of students achieving a score of passing proficiency on annual statewide exams. Specifically, we use the percent passing fourth grade math proficiency (the earliest widely available grade level), which matches the school to which houses are matched. (Math and reading scores are highly correlated.) Because exams may vary between states, we standardize to a z-score within the state, so achievement is measured relative to other fourth graders in the state using the same exam.

Urban Centrality. To account for a neighborhood's job and cultural amenity access, we measure its distance to its metro area's central business district (CBD). We define the point of the CBD by the location of city hall for the largest city in the metro area, which we located manually using Google Maps.[5]

Environmental Quality. We use two dimensions of local environmental quality, hazardous

[5] For a few metros with multiple centers, such as Dallas-Fort Worth, we use the closest large city to the neighborhood. We obtain similar results when defining the CBD by the tallest building in the largest city.

waste exposure and air pollution. We measure hazardous waste by the number of sites on EPA's National Priorities List (NPL, often known as "Superfund") within five kilometers. For air pollution, we use Environmental Protection Agency (EPA) monitoring data on the number of days exceeding safe levels of ozone in 2009. For each neighborhood, we linearly interpolate the three closest monitors, weighting by the inverse of the distance.

Appendix Table B2 reports the mean and standard deviation of each of these amenities, by city. Because all the amenities are in different units, we standardize each measure to a z-score for comparison before estimating our models.

3.3 Regulations and Development Frictions

Zoning. Our measure of regulatory stringency is the Wharton Land Use Regulation Index (WRI) (Gyourko, Saiz, & Summers, 2008), which has become standard in the literature. The WRI is based on surveys of local land use planners, who were asked about their rules on minimum lot sizes, impact fees, time to permit, environmental studies, and so on.

The survey is conducted at the municipal level (i.e., the city or other political unit issuing permits for construction). However, Gyourko et al. (2008) suggest aggregating to the metro area level. We follow this advice in our main models, weighting by the land area of each municipality to form the metro-wide aggregate. All regulation scores are normalized to have mean zero and unit variance within metros. In sensitivity analyses, we use the raw WRI at the municipal level. However, because not every municipality is covered by the survey, these models involve a substantial loss of neighborhood data.

Historical Development. In addition to *de jure* regulation, we investigate whether existing development creates *de facto* barriers to redevelopment by fixing the housing stock in place. To measure this kind of friction, we quantify how much of a market's housing was developed in the distant past, before our sample period. For this, we use county-level census data on the fraction of housing in the 1980 census that was constructed before 1970. This definition provides a metric of how developed an area was in the past, without intermingling the amount of new construction occurring within our sample period.

Appendix Table B3 summarizes the regulations and potential lock-in in our data, by city.

4 Empirical Model

We test three hypotheses generated by our theory. First, we test for the existence of tickets in a nonlinear hedonic model that nests the standard semilog model. Second, we test whether tickets are more likely to emerge in areas with more restrictions on land use, as our theory predicts. Third, we test whether tickets are increasing in amenities. To do all this, we employ a two-stage empirical model. First, we estimate tickets and per-unit prices for each neighborhood. Second, we relate these terms to an index of neighborhood amenities, testing how the contribution varies with market-level restrictions to housing (re)development.

4.1 Two-Stage Model

The first step is to estimate, by city, the pricing function for each neighborhood (i.e. elementary school attendance zone n within city c). We estimate the nonlinear model:

$$p_{icn} = [\alpha_{cn} + exp(\beta_{cn} + H_{icn})]exp(\epsilon_{icn}), \tag{6}$$

where p_{icn} is the price of property i in city c and neighborhood n. Each neighborhood has a ticket price α_{cn} as well as proportionate prices β_{cn} per unit of housing services H. The error, ϵ_{icn}, is normally distributed (so $exp(\epsilon_{icn})$ is log-normal).

This functional form nests the semilog model: when $\alpha_{cn} = 0$, $ln(p_{icn}) = \beta_{cn} + H_{icn} + \epsilon_{icn}$, where the β_{cn} would be neighborhood fixed effects and the H_i is some estimated function of housing services. This restricted model is routinely used in hedonic modeling (e.g. Avenancio-León & Howard, 2022; Banzhaf, 2021). We also maintain the standard assumption that errors are proportionate. In contrast to the standard model, our generalized functional form imposes a constraint that prices be non-decreasing in housing services.

To avoid confusion, it is worth noting that, in their own ways, both α and β could be called "intercepts," in the sense that, at $H = 0$ and $\epsilon = 0$, we have $p_{icn} = \alpha_{cn} + exp(\beta_{cn})$.

Thus, in semilog models that omit α, β too is an intercept. However, the crucial difference, both in interpretation and for identification, is that, at $H > 0$, we have $\partial^2 p/\partial\alpha\partial H = 0$ but $\partial^2 p/\partial\beta\partial H > 0$. Thus, α is a ticket to enter the community that does not vary by H, whereas $exp(\beta)$ has a proportionate effect on the per-unit price of H. Thus, the semilog model cannot capture tickets. This distinction is what allows us to separately identify α and β. However, we acknowledge that we cannot non-parametrically identify a price function $p(H)$ separably from a housing services function $H(X)$, for observables X, a point emphasized by Epple, Quintero, and Sieg (2019) and Landvoigt, Piazzesi, and Schneider (2015). Notably, we do not observe prices at the limit as H shrinks to zero, so cannot literally identify intercepts. Nevertheless, our goal is not to identify intercepts as such, but to characterize how prices vary across neighborhoods with varying G, namely whether G on average shifts the whole function up by a constant or tilts up the slope (or both). Significantly, if what we identify as tickets in our model were merely helping fit a non-linear price function, we would not expect these patterns in capitalization of amenities to vary by land-use restrictions.

We recover each of the two parameters, α_{cn} and β_{cn}, for each neighborhood in the data. These thousands of parameters then become the data points for our second stage estimation, which again is nonlinear:

$$\alpha_{cn} = \alpha_c + (1 + \alpha_z Z_c) \cdot \gamma' G_{cn} \tag{7a}$$

$$exp(\beta_{cn}) = \beta_c + (\beta_0 + \beta_z Z_c) \cdot \gamma' G_{cn}, \tag{7b}$$

where Z_c is a measure of housing development frictions in a city, such as the metro-wide WRI score, and G_{cn} is a neighborhood-level vector of amenities.

The second stage model incorporates three main features. First, it includes an average ticket and price for housing services for each market, respectively α_c and β_c, to account for average differences across metro areas, the direct effects of metro-wide amenities like climate, and the direct effect of development restrictions, Z_c.

Second, it incorporates an index of neighborhood public goods and amenities, $\gamma' G$. We jointly estimate this model with the cross-equation restriction that γ is the same in (7a) and (7b). The direct effects of this index on tickets and proportionate effects, respectively, are captured by the first terms in parentheses, 1 and β_0. The β_0 term is merely a scaling parameter that accounts for differences in units between α (dollars) and β (dollars per H).[6]

Third, the model includes interaction effects for how metro-level housing market restrictions, Z_c, affect the relative capitalization of amenities into tickets or slopes, represented by α_z and β_z, respectively. These terms are the key to our theory about the impact of restrictions on capitalization. Tighter restrictions in the wider market should lead to more stratification among neighborhoods via tickets. If $\alpha_z > 0$, there is more capitalization through tickets. Note that we are not regressing prices on Z, but rather a decomposition of prices (α and β) on an interaction between Z_c and G_{cn}, while absorbing the direct effects of Z_c through city fixed effects. For this section of the paper, we treat G_{cn} as exogenous conditional on the fixed effects, but introduce quasi-experimental variation in Sections 6 and 7.

The second stage regression uses the first stage estimates of ticket and slope parameters as data. Thus, ours is a case of sequential two-step m-estimation, but with many parameters arising in the first stage, making analytic standard errors difficult to obtain. In these cases, Cameron and Trivedi (2005) recommend a bootstrap estimate of the variance of the second stage parameters (Chapter 11, section 2). Treating the first stage estimates as draws from an asymptotically normal distribution, we iteratively draw 300 bootstrap samples from the first stage parameters (including the covariance matrix) and re-estimate the second stage model, producing a distribution of parameter estimates. The robust standard errors reported in Section 5 are calculated from this bootstrapping procedure.

4.2 Housing Services

To estimate the model, we need to specify a housing services index, $H(X_i)$. We consider five possibilities. Model (i), the simplest, uses only the primitive input, land L. Model (ii)

[6] Note that we cannot separately identify an α_0, β_0, and the vector γ to scale, so we set $\alpha_0 = 1$. Additionally, we cannot identify G to location separately from α_c, β_c, and β_0, so γ omits a constant term.

uses living area as the service index, implicitly taking land as an input in its production. Model (iii) uses land but controls for non-land housing characteristics with an additively separable term. These models take the form

$$p_{icn} = [\alpha_{cn} + exp[\beta_{cn} + ln(L_{icn})] + \lambda_c' X_{icn}]exp(\epsilon_{icn}) = [\alpha_{cn} + exp(\beta_{cn})L_{icn} + \lambda_c' X_{icn}]exp(\epsilon_{icn}),$$

where X_{icn} is a vector of housing attributes such as living area, age of structure, and room partitions, and λ_c is a city-specific parameter vector of weights on these attributes. (Our results for model (iii) use a flexible function of living area only, since this attribute is widely available across the cities in our sample, unlike room partitioning.) This model prices the capital component of housing separately from its primitive input, land. An issue with this approach is that by requiring a market-wide price of capital, the models cannot be estimated neighborhood by neighborhood. The increased complexity of estimating this model required breaking the metro areas into additional sub-markets (as detailed in Table B1).

In the remaining two models, the proportionate effect of β is on the bundle of capital as well as land. These models take the form

$$p_{icn} = \alpha_{cn} + exp[\beta_{cn} + \hat{H}_i] + \epsilon_{ic},$$

where $\hat{H}$ is now an index of housing services. The index is a flexible function of housing attributes, $\hat{H} = h(\lambda, X)$, where X are observed property attributes and λ represents parameters. This function is determined in a preliminary estimation of Equation 6, based on a nationally-representative subsample of data. Model (iv) uses land and living area, which are available for most properties. Model (v) additionally uses structure age and room partitions. While this model is more flexible, these attributes are not available for all cities. With these consistent estimates of $\hat{H}_i$, we then estimate Equation 6 on the remaining dataset.

5 Results

5.1 Summary of Tickets in Neighborhood Price

Our estimates of Equation 6 indicate that tickets are pervasive—the α coefficients are rarely zero. Appendix Figures C1 and C2 depict the distribution of t-statistics from the first stage estimates of tickets from Equation 6, for two housing services functions that bracket the range we consider. The results indicate most neighborhoods have positive and statistically significant tickets. Across neighborhoods, the average ticket share of price ($\alpha_n/\bar{p}_n$) ranges from 28% in model (iii) to 80% in model (iv), with other models in between. This is *prima facie* evidence that tickets are present and should be accounted for in hedonic modeling. But are they economically important, and do their patterns conform with our theory?

5.2 Regulation at the Metropolitan Level

To address these questions, the estimated α_{cn} and β_{cn} from the first stage models become the observations for the second stage, represented by Equation 7. Table 1 presents the results using the metro-level regulation index as a measure of zoning. Each column represents a separate regression, each respectively using one of the five measures of housing services $H(X)$. The regression is weighted by the square root of the number of transactions contributing to the first stage estimate. Heteroskedastic-robust standard errors are reported in parentheses.

The first coefficient, α_Z, is the interaction of ticket capitalization with the zoning measure. This coefficient represents a key test of our theory. A positive coefficient indicates that more restrictive zoning induces more capitalization of amenities into tickets. Across all models, we find a positive and statistically significant estimate of α_z, consistent with our theory. This finding implies that, aside from any direct effects of regulation on market-level prices, an increase in amenities increases a neighborhood's ticket price.

The second coefficient, β_0, is a scaling coefficient between dollars in tickets versus dollars per unit of housing. It governs the average slope capitalization of amenities within the city (i.e., conditional on the average slope of the city). Because its scale depends on the housing services index used, its results are difficult to interpret across models, but an illustration presented below provides an intuitive aid.

The third coefficient, β_Z, is the interaction of the zoning measure with the slope estimates. This coefficient has an ambiguous sign in our theoretical model. Empirically, it is estimated to be either slightly positive or essentially zero. Thus, depending on how housing services are specified, zoning may induce slightly more capitalization in per-unit prices. The results do not show, however, that neighborhoods are *less* stratified in prices per unit when zoning is higher, despite their being more stratified via tickets. That is, there does not seem to be a compensating effect of paying less per unit of housing service when paying more at the extensive margin for a high amenity neighborhood.

The last four coefficients comprise the amenity index, $\gamma' G_n$, which includes school test scores, proximity to the central business district, proximity to toxic waste sites, and a measure of air quality. The coefficients are consistent with intuition: the G index is increasing in test scores and decreasing in distance from jobs and pollution.

To help interpret these coefficients, the left panel of Figure 1 plots the model's predicted values as a function of housing services, at two levels of zoning and two levels of amenities. The figure plots results using housing services model (iii), adjusting for housing capital. (Appendix Table C1 provides the components of this graph as well as results for other models.) The median level of housing services is denoted by the vertical line for context. The green curve with hatched markings represents a baseline neighborhood at the 25th percentile of $\gamma' G$. For ease of comparison, we use this same baseline for both levels of zoning.[7] The blue curve with diamond-shaped markings represents a "prime neighborhood" at the 75th percentile of $\gamma' G$ and the average level of the regulatory index ($Z = 0$). The red curve marked with circles represents a prime neighborhood at a one standard deviation higher level of the regulatory index ($Z = 1$).

[7]That is, for this exercise, we keep the "fixed effects" α_c and β_c from Equation 7 constant for all plotted functions, although in principle they could vary with Z_c.

The figure illustrates the importance of tickets in the capitalization function. Critically, the price function in the prime neighborhood (blue curve) is nearly a parallel shift up from the base neighborhood (green curve), with most of the capitalization coming via tickets. At a more stringent level of regulation (red curve), the ticket is slightly greater, as predicted. To focus on the comparison, the right panel takes the difference in the projected prices, plotting the premium associated with the prime neighborhood at each level of zoning. Although the premium does grow slightly as homes increase in size, most of it is realized even at the smallest properties. And, again, this is all the more true in more restrictive areas.

Table 2 presents the numerical values of these premia, again moving from the 25th to 75th percentile of the amenity index. The first row of the table displays the ticket (i.e., when $H = 0$), which is \$31,100 at the average level of zoning. The subsequent rows of the table show how total capitalization (ticket plus slope) varies with property size. Column 1 shows the point in the housing services distribution at which the premium is evaluated. Column 2 shows the base value at the property size, which, when using model (iii), is the land value minus structure value.[8] Column 3 reports the total premium over base value when moving from lesser to greater amenities, at the average level of zoning ($Z = 0$). For example, the median-sized property in the prime neighborhood commands a \$40,200 premium over the base neighborhood, \$31,100 of which is ticket. Even a very small property (the 5th percentile of sizes in a typical city) is due a \$34,200 premium. Column 4 shows the share of the premium made up by the ticket. With some degree of slope capitalization, these shares fall with house size, but even at a median house the ticket represents 77 percent of the total premium.

The remaining columns of the table repeats the exercise for a high-zoning city. In line with our theory, the ticket increases 36 percent to \$42,200, and throughout the property size distribution, tickets make up a greater share than the average zoning city. Thus, tickets are economically important and an inherent part of economics models of land use, as well as

[8] Appendix Table C1 reports on other models which are explicitly or implicitly inclusive of capital. Consequently, their base values are roughly 100 to 150% higher.

statistically significant.

5.3 Regulation at the Municipal Level

The metro area (CBSA) regulatory index, recommended by Gyourko et al. (2008), allows the inclusion of all neighborhoods within a market. It is, however, a coarse measure of the actual regulatory regime a neighborhood faces, because it assigns the same stringency index to all parts of a metro area.

Our next specification uses the finer geography available in the WRI, at the municipality or jurisdiction, to assign a more precise measure of the regulatory stringency applying to a particular neighborhood. This reduces the measurement error in the index Z and permits more variance, as there are more municipalities than metro areas. However, because the WRI surveys a subset of municipalities in each metro area, this restriction causes a substantial loss of sample size—about three quarters of the data available in the metro-level regressions. Some metro areas had to be dropped entirely due to a lack of admissible municipalities.[9]

Table 3 displays the regression results for the municipal-level regulatory index. Despite differences in sample, the results are similar to the metro-level index. More regulated municipalities capitalize amenities into tickets more so than less regulated municipalities ($\alpha_z > 0$), even when comparing among cities *within* the same metro area. Again, at the same time, we do not see less capitalization into the slope of the housing services function (β_z). The similarity of results from the metro and municipal level is further evidence that the model is picking up stratification among neighborhoods according to their market's regulatory environment, not simply that more regulated markets tend to have higher housing prices.

5.4 Historical Frictions

Our theory and the empirical results so far indicate that restrictions inhibiting the adjustment of the housing stock can result in capitalization via tickets. Zoning is a measurable and

[9] A jurisdiction is dropped when it is missing from the WRI survey or when it has only one elementary school (thus eliminating all within-city variation).

policy-relevant friction, but certainly not the only one. We next consider another source: history. Structures are highly durable. Moreover, land division and the associated property rights can lock in a neighborhood to a configuration that outlasts even the structures themselves. If a neighborhood was developed in the more distant past, it is more likely to be farther from the allocation currently optimal, a friction that functions similarly to zoning.

Accordingly, here we substitute an "age of stock" index. To isolate lock-in to past development, in contrast to (the inverse of) recent growth in the housing stock, we leverage historical census records of the housing stock. We use the fraction of housing in the 1980 census that was at least 10 years old (i.e., built before 1970). This provides a metric of how developed an area was several decades prior to our price observations. We use county as the geographic area for age of stock measurement.

Table 4 displays the results of the regression using the age of stock index as the measure of frictions. The pattern is remarkably similar to the regulatory index. Places with development frictions due to older, locked-in development are more likely to capitalize amenities into tickets. There is mixed evidence that age of stock also amplifies capitalization of amenities into per-unit prices of housing services, with some housing services models showing significantly positive coefficients, and others statistically or economically insignificant. Appendix Table C2 displays the implied amenity premium in a typical metro area for the housing stock age model, which follows the patterns of Table 2.

While the correlations of tickets with zoning and historical lock-in make economic sense, ultimately we can be agnostic about their source. Their existence and the fact that they may capture amenities is sufficient justification to relax the standard hedonic model.

6 Estimation of Ticket and Slope Pricing

Having established that tickets are pervasive, stronger in areas where there are more restrictions on development (either *de jure* or *de facto*), and economically important, we revisit the ultimate objective of many hedonic estimation problems: to recover the marginal WTP of amenities. For this purpose, there is no longer any need to interact effects with Z, as we did in Sections 4 and 5. Nor is there necessarily any need to nest the semilog model, a functional form that is convenient but not privileged by any strong theory. In general, little is known about the "right" functional form. But there are some natural starting points. In this section, we suggest some straightforward functions. Accompanying this paper, we provide user-friendly MATLAB and R code to estimate them, which we call the *tixslopes* estimator. Appendix G provides details about the code.

6.1 Introducing the *Tixslopes* Estimator

In what follows, our notation is similar to Section 4, but assumes the analyst is studying a single city c (or, equivalently, estimating separate models by city) and so suppresses that subscript. We also now write α and β as vectors multiplying the vector G. Our first model is linear in all sub-components, α, β, and $H = \lambda' X$ and has additively separable errors:

$$p_{in} = \alpha_0 + \alpha' G_n + (1 + \beta' G_n)(\lambda' X_{in}) + \epsilon_{in}. \tag{8}$$

Note that this model is still nonlinear, as there is an interaction of parameters β and γ, putting them in the class of m-estimators, with nonlinear least squares (NLS) as a natural objective function. (A possible exception is the case where housing services enter as a scalar, e.g. land or a pre-specified index.)

In Equation 8, the linear component $\alpha' G$ is a reasonable choice, as tickets are additively separable by definition. For the slope capitalization and housing services functions, an alternative option is to take the exponential of the linear combinations:

$$p_{in} = \alpha_0 + \alpha' G_n + exp(\beta' G_n) exp(\lambda' X_{in}) + \epsilon_{in}, \tag{9}$$

which is again nonlinear.[10]

[10] The interaction requires some normalization to convert units of G or H into prices. We normalize the values of G to a mean of zero, so that the typical neighborhood has $\beta' G = 0$ in Eq. 8 and $exp(\beta' G) = 1$ in Eq. 9, with housing services converting into dollars.

This option enforces intuitive constraints by imposing non-decreasing capitalization and housing services functions. In the code we provide, the linear and exponential options can be mixed and matched, e.g., $(\beta' G) \cdot exp(\lambda' X)$ or $exp(\beta' G) \cdot (\lambda' X)$.

In addition to these additively separable error structures, our *tixslopes*-estimator also allows for proportionate errors as an option. In the case of Equation 9, specifying proportionate errors nests the semilog model. Additionally, in all cases, our estimator computes robust standard errors allowing for heteroskedastic errors.

Finally, spatial or temporal fixed effects are often used to aid with identification of hedonic WTP estimates of amenities. If such fixed effects are meant to soak up capitalization of non-targeted amenities, then their effects could appear in both tickets and slopes. Conceptually, it is straightforward to incorporate such effects into the pricing function as dummy variables included in $\alpha' G$ and $\beta' G$. The codes we provide allow for the specification of these wider area effects as separate parameters to be estimated in a brute force way in the NLS routine.

However, when the area fixed effects are numerous, computational constraints begin to bind. A notable example is the boundary effects estimator, which pairs two sides of a sharp spatial boundary differing in one amenity but otherwise with approximately the same local attributes. A classic example is sorting on school quality, where the design was pioneered by Black (1999), refined by Bayer et al. (2007) and Kuminoff and Pope (2014), and is still widely used (Zheng, 2022). It also has been used to evaluate the effects of zoning (Turner et al., 2014). We next address a tractable approach to this model.

6.2 Two-Step Estimator for High Dimensional Fixed Effects

In spatial border discontinuity designs, there are a large number of boundary groups, b, and a single amenity of interest (e.g. school quality) varying discretely at the boundaries. Let $S \in G$ be the amenity that varies discretely. This design isolates quasi-experimental variation in S by narrowing the analysis to a band around a sharp, discontinuous change in the amenity at the border, nonparametrically controlling for other factors in the region of the discontinuity that vary continuously. For expositional convenience, in this subsection we discuss the case of additively separable errors, but have derived similar models with proportionate errors, which are included as an option in our *tixslopes* code. We also assume a pre-determined housing services index H.

These models introduce many nuisance parameters. One straightforward option for overcoming this problem is to incorporate the boundary effects into Equation 8:

$$p_{inb} = \delta_b^{\alpha} + \alpha S_n + \delta_b^{\beta} H_{inb} + \beta S_n H_{inb} + \epsilon_i, \tag{10}$$

where α and β capture the capitalization of school quality into tickets and slopes respectively, and δ_b^{α} and δ_b^{α} are boundary fixed effects that capture the way unobservables enter tickets and slopes respectively. This is a high dimensional fixed effects model with interacted regressors, for which well-known methods and codes exist.

The exponential version of ticket capitalization, expanding on Equation 9, is more challenging. We suggest a tractable two-step method. The pricing equation is:

$$p_{inb} = \delta_b^{\alpha} + \alpha S_n + exp(\delta_b^{\beta} + \beta S_n + H_{inb}) + \epsilon_i, \tag{11}$$

which can be represented as:

$$p_{inb} = \bar{\delta}_b^{\alpha} + \bar{\delta}_b^{\beta} exp(H_{inb}) + \epsilon_i^1 + \epsilon_i. \tag{12}$$

The first stage (12) is a linear regression, which ignores the target amenity S, recovering instead the boundary-level ticket and slope parameters, which are composites of observed and unobserved elements. That is, they contain both the unobservable effects δ and the average of the capitalization effects of S. For boundary side weights w_1, w_2 (e.g., the number of observations contributed to the boundary by side 1 and side 2), the step 1 parameters recovered from (12) are:

$$\bar{\delta}_b^{\alpha} = (\delta_b^{\alpha} + w_1 \alpha S_1 + w_2 \alpha S_2) \tag{13a}$$

$$\bar{\delta}_b^{\beta} = exp((\delta_b^{\beta})(w_1 \exp(\beta S_1) + w_2 \exp(\beta S_2)). \tag{13b}$$

Substituting these back into the pricing equation, we get the second stage,

$$p_{inb} = \bar{\delta}_b^{\alpha} - w_1 \alpha S_1 - w_2 \alpha S_2 + \alpha S_n + \frac{\bar{\delta}_b^{\beta} exp(\beta S_n + H_i)}{(w_1 \exp(\beta S_1) + w_2 \exp(\beta S_2))} + \epsilon_i. \tag{14}$$

The target parameters are α, β. The $\bar{\delta}$ parameters are known from the first stage, and the remainder of the equation is data. So, the result is a nonlinear model in just two parameters.[11]

One disadvantage of this approach is that the first stage slopes could be below zero. One could impose the constraint that $\delta_b^{\beta} > 0$ in the first-stage estimation. However, in our application (below) we accept this possible violation since we do not know the true functional form. In a Monte Carlo analysis reported in Appendix E, we find that these functional forms can reasonably approximate WTP even when they are mis-specified—as long as the model allows for tickets. For example, for any of eight data generating processes we consider (linear and exponential housing services, linear and exponential capitalization, and additives and proportional errors), the model based on it approximates the WTP for the other seven models reasonably well. In contrast, the semilog model performs quite poorly, overestimating the extent to which WTP is proportionate in H.

Appendix G details the *tixslopes* code estimator of the boundary effects model, including variants of these models for proportionate errors.

7 Amenity Valuation With a Two-Part Tariff: An Application to School Quality

We now illustrate our proposed approach with an application to school quality valuation. Because our neighborhoods are defined by elementary school attendance zones, access to a school changes discretely at a boundary which is nested within political and zoning jurisdictions, so other amenities vary more continuously at the neighborhood boundary. Accordingly, we use the above boundary indifference approach.

[11] In practice, we also allow for a constant in the estimation of (14), merely for flexibility, but these are often at or very near zero.

We compare hedonic WTP estimates from ticket-accommodating models with the standard semilog model. We do this comparison across our sample of nationwide housing markets. We estimate one metro area at a time, recovering the citywide average WTP implied by each model. Table B4 summarizes the data in our application, including the number of schools and boundaries, by city, as well as sample size and normalized school quality.[12]

7.1 Modeling Strategy

The standard semilog version of the boundary discontinuity method is

$$\ln p_{inc} = \tilde{\beta} S_n + \tilde{\delta}_b + \gamma H_i + \tilde{\epsilon}_i \tag{15}$$

where boundary area effects are captured by $\tilde{\delta}_b$ and the capitalization rate for market c is $\tilde{\beta}_c$. From this, we can calculate the capitalization of a one standard deviation change in school quality in percentage terms, $^{p(H,S=1)}/_{p(H,S=0)} = exp(\tilde{\beta})$. (Note for later that this is a *constant* premium.) The premium in dollars, at a property of size H, is then $\Delta p(H) = E\big(p(S = 1, H) - p(S = 0, H)\big) = \big(exp(\tilde{\beta} + H) - exp(H)\big)E(exp(\tilde{\epsilon})) = exp(\tilde{\beta})exp(H)E(exp(\tilde{\epsilon}))$.

The alternative, ticket-accommodating models are the high-dimensional fixed effects model of Equation (10) and the two-step nonlinear model of Equations (11)–(14), with separate parameters estimated for each metro area (CBSA) and with housing services model (iv) from Section 4.2. In these models, the capitalized value of a one standard deviation change in school quality at a property of size H is $\Delta p(H) = E\big(p(S = 1, H) - p(S = 0, H)\big) = \alpha_c + \beta H$ for the linear model and $\Delta p(H) = E\big(p(S = 1, H) - p(S = 0, H)\big) = \alpha_c + (exp(\beta_c) - 1)exp(H)$ for the exponential model.

Note that the semilog model imposes a premium that is constant in percentage terms, as it is governed by only one parameter ($\tilde{\beta}$). The tickets-and-slopes models do not impose this, and in fact, in what follows, we find the assumption of a constant proportional premium is frequently violated. We find this has implications for WTP estimates for homes of different

[12] As discussed in Section 3.2, we lose some markets with insufficient coverage in the school attendance zone boundary data, as we need precise geography of attendance boundaries (see also Table B4).

sizes. Appendix D discusses in more detail how the semilog model will, in the presence of non-negative tickets, match the average amount of capitalization but will tilt the pricing function too steeply, understating WTP for small properties and overstating WTP for large properties.

7.2 Results

Table 5 shows the average WTP estimate across all markets for each model for three points on the housing services distribution, the 25^{th}, 50^{th}, and 75^{th} percentiles of home size (percentiles taken within each market). There are columns for WTP in 2010 dollars and the value as a proportion of the baseline price. Price premia, $\Delta p(h)$, are estimated as present values for a permanent one standard deviation increase in school quality relative to an average school quality. We show results for the semilog model (adjusting the expected value for Jensen's inequality using either homogeneous or heteroskedastic error variances). We also show results for our two proposed estimators, which are remarkably similar (though slightly higher on average for the linear model).

The typical WTP ranges across models from about \$6,000 for a 25^{th} percentile property to \$7,000 to \$8,000 for a 75^{th} percentile property, a range consistent with the range of \$9,000 to \$15,800 reported for five cities in Kuminoff and Pope (2014), as well as Bayer et al.'s (2007) preferred estimate of \$7,900 for the San Francisco Bay area.[13]

Of course, the equilibrium WTP for an amenity can vary across markets based on economic conditions. Separate results for each market are reported in Appendix Table F1. Appendix Figure F1 plots the point estimates of the models for the median-size property,

[13]Our models' estimates for the value at a median-sized home in San Francisco range from \$9,000 to \$11,300 (Appendix Table F1). Our figure for Bayer et al. comes from \$19.70 per month from their Table 7, Col. 4. We inflate it from 1990 to 2010 dollars (a factor of 1.67) and divide by a monthly discount rate of 5%/12. Kuminoff and Pope (2014) report values for a percentage change in test scores, not standard deviations, so their estimates are not directly comparable to ours. However, they compute how their estimates compare to Bayer et al.'s, so we can combine their computed ratios with our value from Bayer et al.

across markets. (Other points in the property size distribution show similar patterns.) Regardless of a city's average WTP, the models produce similarly-ordered price premia across markets. If one city has a high premium in the semilog model, it tends to also have a high premium in the tickets-and-slopes models too.

Where the models do diverge from each other is within city, across the housing services distribution. As Table 5 shows, compared with the semilog model, the tickets-and-slopes models tend to have a flatter profile of the premium as properties increase in size, meaning the school quality premium comprises a larger percentage of the value of smaller properties. This is a consequence of the semilog model imposing a constant percentage premium for all properties, regardless of size, whereas the ticket-accommodating models allow the proportional premium to vary. Appendix Figure F2 shows directly how the hedonic estimate from a ticket-accommodating model violates the constant-percentage premium assumption in most markets.

Figure 2 demonstrates the pattern by plotting the distribution of the difference in premium between 75^{th} and 25^{th} percentile sized properties. With the premium denoted, $\Delta p(H_q) = p(H_q, S = 0) - p(h_q, S = 1)$ for a property in size percentile q, the figure shows differences in premium scaled by the premium of the average property, $\frac{\Delta p(H_{75}) - \Delta p(H_{25})}{\Delta p(H_{50})}$. (The unscaled difference exhibits a similar pattern.)

The figure shows the distribution of gaps in the tickets-and-slopes models are to the left of the semilog model. That is, when capitalization is permitted in tickets, the amenity premia generally rise more slowly in housing size, so the difference between the premium in a large home and a small home is diminished. As is to be expected with a random variable, there are exceptions, as in some markets the premia actually rise more steeply when tickets are permitted, and some estimates even show negative gaps. But even these gradients are only revealed in the more flexible tickets-and-slopes models. Overall, the figure clearly shows that the constant-percentage premium induced by the semilog model is frequently violated by the presence of tickets.

7.3 Implications for Policy Valuation

Ticket capitalization implies a flatter profile of amenity value in home size, so a change in amenities may affect smaller properties relatively more than otherwise predicted. To explore the implications of this pattern in our application, we run a simple experiment on the cities in our school boundary sample. We introduce a one-tenth standard deviation increase in school quality for all neighborhoods with below-average quality ($S < 0$), and then, using the WTP estimates above, we evaluate the implied change in home price this would induce, comparing across models. We then sum up the valuation changes to all affected properties and calculate the fraction of the amenity valuation that accrues to small properties (below median home size). We compare the two ticket-accommodating models to the semilog valuations. For the semilog valuation, we use two possibilities: the percentage increase to a property's observed price (including the residual, i.e., implicitly inclusive of its unobservable attributes), $[exp(\hat{\beta} \cdot 0.1) - 1]p_i$, and the percentage increase to its projected values (i.e., exclusive of its residual), $[exp(\hat{\beta} \cdot 0.1) - 1]exp(\hat{\beta} S_i + \tilde{\delta}_b + \gamma H_i)$.

Figure 3 plots the distribution across cities in the share of the capitalization that accrues to small properties. When using the semilog model, the median fraction of capitalization accruing to small properties is 51 percent. This reflects cross-cutting patterns–that there are more small properties in neighborhoods with below average test scores (hence, receiving the positive innovation), but they tend to be lower value by definition. The median fraction rises to 54 percent when using capitalization over projected values (exclusive of unobservables).

When using the ticket-accommodating models, the fraction of capitalization accruing to small properties is higher. The figure shows both the nonlinear and linear ticket models have distributions to the right of the semilog model. The median fraction of capitalization to small properties is 58 percent in the linear ticket model and 63 percent in the nonlinear model.

In summary, a model with tickets implies residents of smaller properties place a higher value on school quality than does the semilog model, a fact with potentially far-reaching implications for the economics of local public goods. The misspecification in the semilog model may understate the value of school quality to owners of smaller properties, and consequently lead researchers to understate the distributional implications of such an intervention.

8 Conclusions

This paper addresses how local public goods are capitalized, through ticket prices at the extensive margin or the slope of the land/housing price function at the intensive margin. We find evidence of both. Additionally, we find that more regulated cities and cities with more historical lock-in exhibit more capitalization in ticket prices, in line with the idea that constraints on housing units generate a separate shadow price on them.

Our first contribution has been to demonstrate how capitalization of amenities "works" in the presence of zoning and other land-use restrictions (and, vice versa, how the effect of zoning depends on amenities). Beyond this basic point, our work has three further implications. First, our paper suggests that the standard semilog hedonic model may be badly mis-specified in the presence of tickets, especially relevant in the valuation of heterogeneous property value impacts. Relative to a more general model that accounts for tickets, we find that the semilog model substantially overstates the estimated WTP of residents of large properties relative to residents of small properties. Public policies that improve public goods like school quality in poorer, low-value housing areas thus have much greater private benefits to poor households than standard models would suggest.

Second, the presence of tickets could have similarly important implications for the distributional welfare effects of gentrification. Suppose an area receives an exogenous increase of amenities, leading to increased housing costs. As the literature has already recognized, if the marginal bidder moving in during gentrification increases housing prices by more than poorer incumbents' willingness to pay for the increased amenity, incumbent renters could be made worse off (e.g. Banzhaf, Ma, & Timmins, 2019). Capitalization into tickets is likely to augment this effect. The increased housing costs enter as a lump sum effect, rather than proportionate to housing, making the gentrification effect even more regressive.

Third, our findings have implications for old debates between the "new" and the "benefit" views of the property tax—debates about whether the gross-of-tax price of housing simulates a market for public goods, as Tiebout (1956) envisioned. In the presence of congested publicly provided goods, efficiency requires pricing access to the goods per se—not just land—to close the commons (Banzhaf (2014); Calabrese et al. (2011); Fischel (1985)). We suggest that future work evaluating the normative aspects of spatial sorting should consider two-part pricing. Our results are consistent with the notion that zoning creates the ticket price *necessary* for efficient pricing of congested public goods. Nevertheless, the existence of such capitalization is not *sufficient* evidence that public goods are allocated optimally. In particular, our model predicts capitalization into ticket prices in the presence of restrictions on the number of lots, regardless of whether the public good is congested, but such pricing is only optimal in the presence of congestion.

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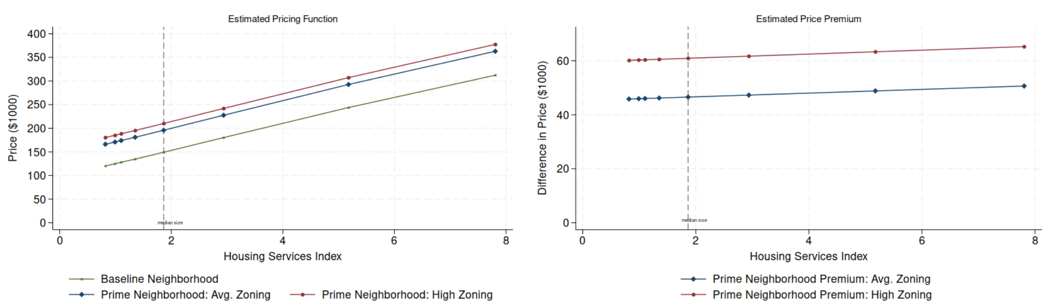
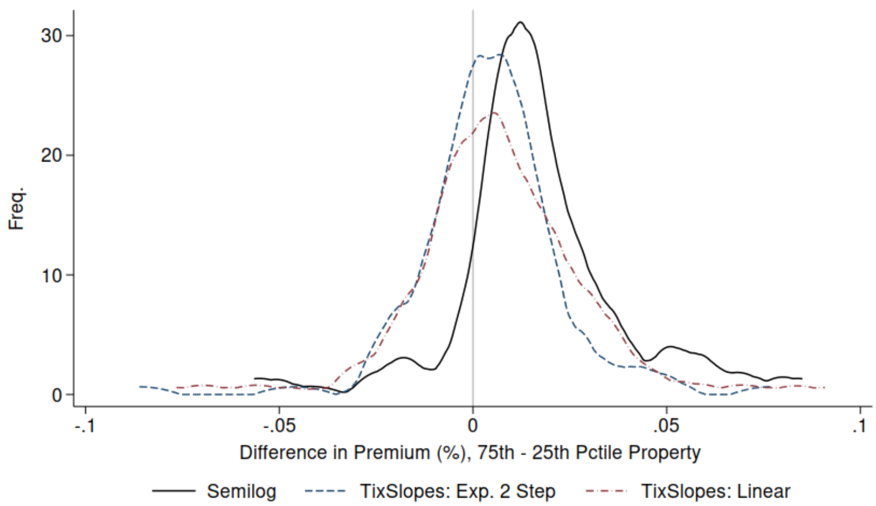
Figure 1: The Value of Housing Services



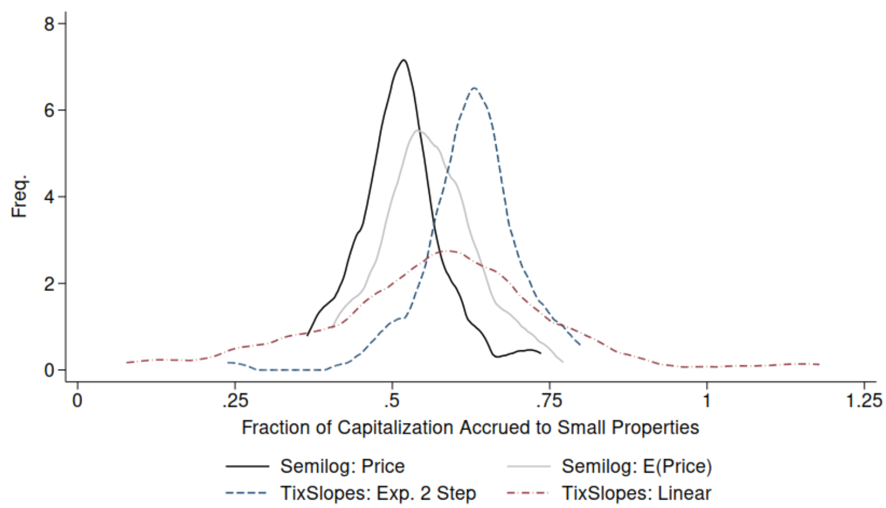
NOTES: The figure portrays the housing price function for a baseline (lower amenity index, 25th percentile) and prime (higher amenity index, 75th percentile) neighborhood, in a typical (mean regulation) city and a more regulated (1 s.d. higher WRI index) city. The figure uses point estimates from Table 1.

Figure 2: Difference in Premia Estimates for Large and Small Properties



NOTES: The figure portrays the distribution across cities in the difference in estimated willingness-to-pay between a 75th percentile-sized property and a 25th percentile-sized property, scaled by the WTP for a 50th percentile property, for the models described in Section 7.1.

Figure 3: Fraction of School Intervention Accruing to Small Properties



NOTES: The figure portrays the distribution across cities of the fraction of a school quality intervention accruing to below-average sized homes. The experiment increases school quality of low-performing schools by 0.1 s.d. The valuation effects are projected using each model's WTP estimate, summed within market, and expressed here as the proportion accruing to below-median-sized homes.

Table 1: Capitalization Function Regression Model: Metro-Level Zoning

Specification	Land Only (i)	Living Area (ii)	Land, Capital Adj. (iii)	Land & Liv. Area (iv)	Property Attributes (v)
α_Z	0.313	0.190	0.355	0.316	0.272
	(0.004)	(0.012)	(0.003)	(0.002)	(0.001)
β_0	0.037	0.737	0.032	0.015	-0.011
	(0.001)	(0.015)	(0.001)	(0.001)	(0.000)
β_Z	0.000	0.257	0.008	0.001	0.000
	(0.001)	(0.006)	(0.000)	(0.001)	(0.000)
Test Scores	32.905	14.134	22.718	33.928	49.862
	(0.318)	(0.295)	(0.084)	(0.094)	(0.089)
Dist. to CBD	-4.435	-5.140	-9.714	-9.908	-11.979
	(0.130)	(0.146)	(0.070)	(0.072)	(0.080)
NPL Sites	-9.105	-1.395	-4.104	-10.592	-15.111
	(0.597)	(0.352)	(0.386)	(0.431)	(0.303)
Ozone Days	-1.575	-0.504	-1.201	-1.963	-2.218
	(0.200)	(0.141)	(0.071)	(0.074)	(0.076)
Fixed Effects	City	City	Submkt	City	City
Cities	141	141	141	140	114
Submarkets			282		
N'hoods	23,707	23,652	23,643	23,620	18,660

NOTES: The table reports results from equations 7 using metro-level measures of regulation. The data are obtained from first stage estimates according to equation 6, using neighborhood-level observation counts as weights. Standard errors are obtained via bootstrapping, sampling 300 replications from the distribution of first stage estimates.

Table 2: Capitalization Function Under Metro-Level Zoning

		Average Zoning		High Zoning	
Property Size (pctile) (1)	Base Land Value ($ 1000) (2)	Premium ($ 1000) (3)	Ticket Share (4)	Premium ($ 1000) (5)	Ticket Share (6)
Ticket Value:		31.1		42.2	
5	54.5	34.2	0.909	46.0	0.916
10	57.0	35.7	0.870	48.0	0.879
25	60.1	37.6	0.828	50.2	0.839
50	63.8	40.2	0.774	53.5	0.788
75	71.5	46.3	0.672	61.2	0.689
90	89.1	63.9	0.487	83.2	0.507
95	105.1	85.7	0.363	110.4	0.382

NOTES: The table reports the housing price function at various points in the housing services distribution for a baseline (lower amenity index, 25th percentile) and prime (higher amenity index, 75th percentile) neighborhood, in a typical (mean regulation) city and a more regulated (1 s.d. higher WRI index) city. The table uses point estimates from Table 1, model (iii), "Land, Capital Adjusted."

Table 3: Capitalization Function Regression Model: Municipal-Level Zoning

Specification	Land Only (i)	Living Area (ii)	Land, Capital Adj. (iii)	Land & Liv. Area (iv)	Property Attributes (v)
α_Z	0.123	0.254	0.152	0.208	0.167
	(0.013)	(0.016)	(0.011)	(0.005)	(0.004)
β_0	0.056	0.877	0.050	0.052	-0.008
	(0.006)	(0.021)	(0.002)	(0.002)	(0.000)
β_Z	0.030	0.057	0.029	-0.010	-0.002
	(0.005)	(0.013)	(0.002)	(0.002)	(0.000)
Test Scores	24.467	10.118	19.157	24.346	38.011
	(0.464)	(0.155)	(0.176)	(0.132)	(0.151)
Dist. to CBD	-2.459	-3.716	-10.546	-8.327	-11.660
	(1.190)	(0.176)	(0.241)	(0.244)	(0.262)
NPL Sites	-14.195	-3.488	-8.357	-13.023	-21.599
	(0.747)	(0.267)	(0.580)	(0.474)	(0.411)
Ozone Days	-5.600	-3.156	-4.068	-6.329	-10.385
	(0.629)	(0.114)	(0.138)	(0.144)	(0.167)
Fixed Effects	City	City	Submkt	City	City
Cities	93	93	93	93	71
Submarkets			178		
Municipalities	499	497	493	498	368
N'hoods	6,400	6,373	6,399	6,374	4,463

NOTES: The table reports results from equations 7 using municipal-level measures of regulation. The data are obtained from first stage estimates according to equation 6, using neighborhood-level observation counts as weights. Standard errors are obtained via bootstrapping, sampling 300 replications from the distribution of first stage estimates.

Table 4: Capitalization Function Regression Model: Housing Stock Development Age

Specification	Land Only (i)	Living Area (ii)	Land, Capital Adj. (iii)	Land & Liv. Area (iv)	Property Attributes (v)
α_Z	0.181	0.286	0.246	0.131	0.107
	(0.078)	(0.200)	(0.003)	(0.001)	(0.000)
β_0	0.039	0.715	0.030	0.007	-0.009
	(0.017)	(0.189)	(0.027)	(0.001)	(0.000)
β_Z	-0.008	0.151	0.007	0.041	0.002
	(0.020)	(0.026)	(0.032)	(0.001)	(0.000)
Test Scores	37.612	16.345	24.786	40.761	57.554
	(1.314)	(1.520)	(0.095)	(0.074)	(0.055)
Dist. to CBD	-5.577	-6.462	-5.418	-12.302	-14.222
	(10.07)	(9.424)	(0.388)	(0.076)	(0.058)
NPL Sites	-15.352	-4.413	-5.153	-18.621	-22.623
	(10.74)	(8.388)	(0.503)	(0.444)	(0.280)
Ozone Days	-0.968	-0.923	-0.926	-1.992	-1.073
	(5.342)	(4.217)	(0.088)	(0.077)	(0.058)
Fixed Effects	Submkt	Submkt	Submkt	Submkt	Submkt
Cities	145	145	145	144	118
Submarkets	197	197	286	196	154
N'hoods	23,897	23,898	23,723	23,896	18,925

NOTES: The table reports results from equations 7 using county-level measures of historical development. The data are obtained from first stage estimates according to equation 6, using neighborhood-level observation counts as weights. Standard errors are obtained via bootstrapping, sampling 300 replications from the distribution of first stage estimates.

Table 5: Summary of Hedonic Willingness to Pay Estimates for School Quality

Average Estimates Across Markets						
	Premium($ 1,000)			Pct. Premium		
Property Size Pctile	25^{th}	50^{th}	75^{th}	25^{th}	50^{th}	75^{th}
Model						
Semilog (Homoscedastic Err. Adj.)	6.08	6.78	7.969	0.039	0.039	0.039
Semilog (Heteroscedastic Err. Adj.)	5.79	6.74	8.322	0.039	0.039	0.039
TixSlopes: Exp. 2-Step	6.27	6.57	7.231	0.036	0.035	0.033
TixSlopes: Linear	6.49	6.77	7.424	0.036	0.035	0.034

NOTES: The table reports the mean WTP estimate from each model described in Section 7.1 for properties at the 25th, 50th, and 75th percentile of the housing services distribution (model *iv*), with percentiles taken within city.

Supplementary Appendices

A Theory: Proofs and Extensions

A.1 Proof of Existence of a Two-Part Pricing Equilibrium in the Presence of Housing Constraints

Our strategy will be to show that there is a decreasing function $\tilde{\beta}(\alpha)$ that clears the housing market and likewise a decreasing function $\tilde{\alpha}(\beta)$ that meets the land use constraint, which may not always be binding. Using these functions, we will then prove the existence of a fixed point $\beta^* = \tilde{\beta}(\alpha^*), \alpha^* = \tilde{\alpha}(\beta^*)$. We proceed with a series of lemmas.

Lemma 1. Fixing G, for any α there is a $\tilde{\beta}(\alpha) \geq 0$ such that

$$\int_{i \in \mathcal{C}(\alpha, \tilde{\beta}, G)} h^{D,i}(y - \alpha, \tilde{\beta}) di = h^s(\tilde{\beta}), \tag{A1}$$

thus satisfying condition 4. Likewise, for any β, there is an $\tilde{\alpha}(\beta) \geq 0$ defined as:

$$\tilde{\alpha}(\beta) = inf \left\{ \alpha \geq 0 \;\middle|\; \int_{i \in \mathcal{C}(\tilde{\alpha}, \beta, G)} di \leq L \right\}. \tag{A2}$$

It is the lowest non-negative value of α satisfying condition 5.

Proof of Lemma 1. The existence of $\tilde{\beta}(\alpha)$ follows from the standard argument for existence of partial equilibrium at a non-negative price, with α (which is here fixed) merely playing the role of shifting the effective income distribution. Market demand is continuous and decreasing in β because $\mu(\mathcal{C})$ is continuously decreasing (Assumptions 2 and 3) and $h^{D,i}$ is too (Assumption 4). It is non-negative (and strictly positive if anybody lives in the city) and bounded (Assumption 4). Housing supply is continuously increasing with $h^S(0) = 0$ and is also bounded (Assumption 1). Together, these guarantee a non-negative $\tilde{\beta}$ exists. (Note that if α is sufficiently high, $\tilde{\beta}(\alpha)$ may be zero, which still satisfies Condition 4.) The existence of $\tilde{\alpha}(\beta) \geq 0$ similarly follows from the continuity of $\mathcal{C}$, the fact that V is decreasing in α, and the fact that WTP for G is bounded (Assumptions 2 and 3). Thus, for any $\{\alpha, \beta\}$, if Condition 5 is violated, we can keep increasing α until it is just satisfied.

Lemma 2. The functions $\tilde{\alpha}(\beta)$ and $\tilde{\beta}(\alpha)$ are continuous and strictly decreasing.

Proof of Lemma 2. Continuity follows immediately from the continuity of $\mu(\mathcal{C})$, market demand for housing, and housing supply, which were established in the proof of Lemma 1, together with the implicit function theorem. $\tilde{\alpha}(\beta)$ is decreasing because, by Assumption 3, $\mu(\mathcal{C})$ is decreasing in both α and β (fewer people want to live in the city when either increases), thus as β increases we can reduce α to maintain Condition 5, the constraint at L. Likewise, $\tilde{\beta}(\alpha)$ is decreasing for the same reason, plus the fact that housing is a normal good (Assumption 4), so those who do continue to live in the city decrease their housing demand. Thus, market demand is lower at higher α and the equilibrium price β falls.

Lemma 3. There is an $\bar{\alpha}$ defined at $\beta = 0$ by

$$\bar{\alpha} = inf\left\{\alpha \geq 0 \,\middle|\, \int_{i \in \mathcal{C}(\bar{\alpha},0,G)} h_i^D(y - \bar{\alpha}, 0)di = h^s(0) = 0\right\}. \tag{A3}$$

So $\tilde{\beta}(\alpha) = 0 \;\forall\; \alpha \geq \bar{\alpha}$. That is, there is a sufficiently high α that will choke off all demand for housing in the city, thus satisfying Condition 4 even at $\beta = 0$. Moreover, $\bar{\alpha} > \tilde{\alpha}(0)$, thus satisfying Condition 5 as well as 4.

Likewise, there is a $\bar{\beta}$ defined at $\alpha = 0$ by

$$\bar{\beta} = inf\left\{\beta \geq 0 \,\middle|\, \int_{i \in \mathcal{C}(0,\bar{\beta},G)} di \leq L)\right\}. \tag{A4}$$

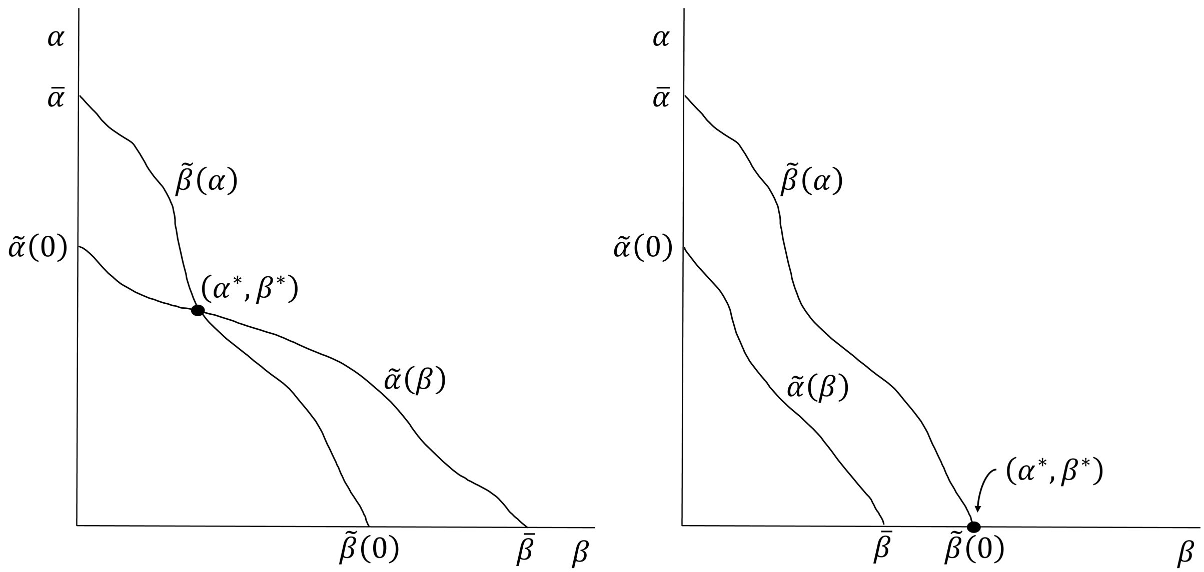
Or, $\tilde{\alpha}(\beta) = 0 \;\forall\; \beta \geq \bar{\beta}$. That is, there is sufficiently high β to just meet Condition 5 on lots without needing $\alpha > 0$, though perhaps not clearing the housing market.

Proof of Lemma 3. The existence of $\bar{\beta}$ is guaranteed by the last part of Assumption 3. The existence of $\bar{\alpha}$ follows trivially from the fact that the support of y is bounded (Assumption 2). Thus, we could always set $\bar{\alpha} = \bar{y}$ if we need to. (Alternatively, it also follows from the fact that housing demand and WTP for G are bounded from above [Assumptions 3 and 4], so there is a finite consumer surplus that each household gets for living in the city, which can be taken away with sufficiently high α.) Crucially, $\bar{\alpha} > \tilde{\alpha}(0)$. Because $\bar{\alpha}$ chokes off all housing demand at $\beta = 0$, we know Condition 5 is satisfied with the inequality being strict. Thus, starting from that point, we can reduce $\tilde{\alpha}(0)$ and still satisfy Condition 5.

Remark 1. Because $\bar{\alpha} > \tilde{\alpha}(0)$, the domain of $\tilde{\beta}(\alpha)$ can be restricted to the interval $[0, \bar{\alpha}]$.

Remark 2. With respect to $\bar{\beta}$, we can have either of two cases: (i) $\bar{\beta} > \tilde{\beta}(0)$ or (ii) $\bar{\beta} \leq \tilde{\beta}(0)$. Under case (ii), it is obvious that $\tilde{\alpha}(\beta) = 0 \;\forall\; \beta \in [\bar{\beta}, \tilde{\beta}(0)]$. Because it is already satisfied at $\{0, \bar{\beta}\}$ by definition, Condition 5 remains satisfied as β increases further to meet Condition 4, without having to increase α above zero. Thus, the domain of $\tilde{\alpha}(\beta)$ can be restricted to the interval $[0, max\{\bar{\beta}, \tilde{\beta}(0)\}]$.

Figure A1: A Fixed Point $\{\alpha^*, \beta^*\}$ Exists



NOTES: The left panel depicts an interior equilibrium with positive tickets ($\alpha^* > 0$). The equilibrium is at the fixed point $\tilde{\alpha}(\beta^*) = \alpha^*$, $\tilde{\beta}(\alpha^*) = \beta^*$. The right panel depicts a degenerate equilibrium with tickets equal to zero.

Thus, we have established that there is a continuous mapping from the non-empty, convex, compact set formed by the Cartesian product $[0, max\{\bar{\beta}, \tilde{\beta}(0)\}] \times [0, \bar{\alpha}]$ to itself. By Brouwer's Theorem, a fixed point $\{\alpha^*, \beta^*\}$ exists. This completes the proof.

Figure A1 illustrates the intuition of the proof. The left panel illustrates case (i). $\tilde{\alpha}(\beta)$ is strictly positive at $\beta = 0$, decreasing, and equal to zero at $\bar{\beta}$. $\tilde{\beta}$ is strictly positive at $\alpha = 0$, decreasing, and equal to zero at $\bar{\alpha}$, with $\tilde{\beta}(0) < \bar{\beta}$ and $\tilde{\alpha}(0) < \bar{\alpha}$. Thus, the two "reaction functions" cross at a fixed point $\alpha^* = \tilde{\alpha}(\beta^*) > 0, \beta^* = \tilde{\beta}(\alpha^*) > 0$.

The panel on the right illustrates case (ii). Everything is the same as case (i), except now $\bar{\beta} \leq \tilde{\beta}(0)$. Recalling from Remark 2 that $\tilde{\alpha}(\beta) = 0 \; \forall \; \beta \in [\bar{\beta}, \tilde{\beta}(0)]$, we have a fixed point $\alpha^* = 0, \beta^* = \tilde{\beta}(0) > 0$. This is the trivial case where Condition 5 on housing units is not binding, so we have no tickets.

A.2 Proof of Capitalization of Amenities into Tickets

For concreteness and simplicity, we prove Theorem 2 for the case of sorting on y. The case of sorting on ϕ is identical, *mutatis mutandis.*

In this case, the set $\mathcal{C}$ of households choosing to live in the city is represented by the interval $[\tilde{y}, \bar{y}]$. Note that, because V is increasing in G and decreasing in α and β, $\tilde{y}$ is continuously decreasing in G and continuously increasing in α and β. Equilibrium Conditions 4 and 5 become respectively:

$$\int_{\tilde{y}(\alpha,\beta,G)}^{\bar{y}} h_i^D(y-\alpha,\beta)f(y)dy = h^s(\beta) \tag{A5}$$

and

$$\int_{\tilde{y}(\alpha,\beta,G)}^{\bar{y}} f(y)dy \leq L. \tag{A6}$$

We will refer to the initial condition as state 0 and the *ex post* as state 1. As implied by Assumption 1, we start with an initial condition where G^0 is higher than the outside option, which is needed to avoid a discontinuity in the sorting equilibrium where the two locations have identical G (Banzhaf & Walsh, 2008). Then as previously established we have $\beta^0 > 0$ and $\alpha^0 \geq 0$.

With these introductory comments, we are ready to prove the theorem.

Proof. We begin with the case where $\alpha^0 > 0$ (i.e., the constraint on lots is binding). Suppose G increases from G^0 to G^1 but α remains unchanged (below, we also consider the possibility that α falls). By Assumption 2′ (continuity), after a *ceteris paribus* increase from G^0 to G^1, there are now some households who formerly preferred the outside option who now prefer the city. Without an adjustment to β, there would be excess demand for housing and the population would exceed L, violating Conditions A5 and A6. Clearly, β must increase. By Lemma 1, there is a $\tilde{\beta}(\alpha^0; G^1) > \beta^0$ that satisfies Condition A5, with the quantity of housing supplied increasing to meet the increase in demand. However, because α is unchanged but β is higher, and because h_i^D is decreasing in β, it follows that to meet Condition A5, $\tilde{y}(\alpha^0, \tilde{\beta}(\alpha^0, G^1), G^1) < \tilde{y}^0$: we must have more people in the city to have sufficient demand to clear the market. Because it was initially binding, clearly Condition A6 is now violated. Thus, we cannot have an equilibrium where α stays constant.

What about the possibility that α actually *falls* and β increases even more to offset this effect? To consider this possibility, begin from the previous point and consider additional adjustments with decreasing α. By itself, this would worsen the violation of Condition A6. So β must increase *at least* as much to leave individuals at the boundary $\tilde{y}$ indifferent—more if we are to restore Condition A6. Thus, households with $\tilde{y}$ experience a real increase in housing prices and a decrease in utility (or decline in real income). Both effects lead to a fall in housing demand for households with $\tilde{y}$. Households with $y > \tilde{y}$ experience the same increase in housing prices and an even greater decline in utility, as they consume more housing.[14] Thus, there is an aggregate decline in housing in the city, which now violates Condition A5. Thus, we have a contradiction. When the constraint on lots is binding, there

[14]Note that at any y the change in β needed to offset a change in α is $\frac{d\beta}{d\alpha}|_{V(y)} = \frac{V_y}{V_\beta}$ which by Roy's identity

can be no equilibrium with a combined increase in G without an increase in α_1.

Finally, when the constraint on lots is not binding, as explained in the text α must be zero. Therefore, it cannot fall further with an increase in G as long as it remains non binding. If it becomes binding, the logic above applies.

This completes the proof.

A.3 Sorting on Two Dimensions

In this subsection, we elaborate Section 2.3's discussion of the potential second-order feedback effects on housing demand when there is sorting on more than one dimension. We extend the model to sorting on y *and* ϕ with the following assumptions.

6′ The continuum of households $\mathcal{I}$ is described by a joint distribution of two parameters, y_i and a taste parameter for G, ϕ_i, which are continuously distributed on the interval $(0, \bar{y}]$ and $[\underline{\phi}, \bar{\phi}]$, respectively, with $\underline{\phi} \geq 0$. This distribution has continuous density $f(y, \phi)$.

7′ $V^i(y-\alpha, \beta, G; \phi)$ satisfies the single crossing property, such that $\frac{\partial(-V_G/V_p)}{\partial y} > 0$ and $\frac{\partial(-V_G/V_p)}{\partial \phi} > 0$. It ensures that $\forall\ \phi$, there is a $\tilde{y}(\alpha, \beta, G; \phi)$ such that all households with $y_i \geq \tilde{y}$ prefer the city to the outside option. Similarly, $\forall\ y$, there is a $\tilde{\phi}(y-\alpha, \beta, G)$ such that all households with $\phi_i \geq \tilde{\phi}$ prefer the city.

Consider a combination of dG and $d\beta$ that leaves Condition 5 just binding (no change in population) without any increase in α. Then we must have:

$$\frac{\partial \int_0^{\bar{y}} \int_{\tilde{\phi}(y,\alpha,\beta,G)}^{\bar{\phi}} f(y,\phi) d\phi dy}{\partial \beta} d\beta + \frac{\partial \int_0^{\bar{y}} \int_{\tilde{\phi}(y,\alpha,\beta,G)}^{\bar{\phi}} f(y,\phi) d\phi dy}{\partial G} dG = 0. \tag{A7}$$

Using Leibniz's rule and re-arranging, we can derive the rate at which prices must increase to maintain this condition:

$$\frac{d\beta}{dG}|L = -\frac{\int_0^{\bar{y}} f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial G} dy}{\int_0^{\bar{y}} f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial \beta} dy}. \tag{A8}$$

Consider now what happens to aggregate housing demand for a given change in β and

is equal to $-\frac{1}{h^D(\tilde{y}-\alpha,\beta)}$. Because housing is a normal good, households with $y > \tilde{y}$ need a smaller *increase* in β to offset the *fall* in α. At the β needed to keep households at $\tilde{y}$ indifferent, richer households are made worse off.

G. We have:

$$dh^D = \frac{\partial \int_0^{\bar{y}} \int_{\tilde{\phi}(y,\alpha,\beta,G)}^{\bar{\phi}} h^D(y-\alpha,\beta) f(y,\phi) d\phi dy}{\partial \beta} d\beta + \frac{\partial \int_0^{\bar{y}} \int_{\tilde{\phi}(y,\alpha,\beta,G)}^{\bar{\phi}} h^D(y-\alpha,\beta) f(y,\phi) d\phi dy}{\partial G} dG. \tag{A9}$$

Substituting Equation A8 into Equation A9, the change in housing demand for a change in G when β changes to maintain Condition 5 is:

$$\frac{dh^D}{dG} = -\frac{\partial \int_0^{\bar{y}} \int_{\tilde{\phi}(y,\alpha,\beta,G)}^{\bar{\phi}} h^D(y-\alpha,\beta) f(y,\phi) d\phi dy}{\partial \beta} \frac{\int_0^{\bar{y}} f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial G} dy}{\int_0^{\bar{y}} f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial \beta} dy} + \frac{\partial \int_0^{\bar{y}} \int_{\tilde{\phi}(y,\alpha,\beta,G)}^{\bar{\phi}} h^D(y-\alpha,\beta) f(y,\phi) d\phi dy}{\partial G}. \tag{A10}$$

Again using Leibniz's rule, this is equivalent to

$$\frac{dH^D}{dG} = \left[\int_0^{\bar{y}} h^D(y-\alpha,\beta) f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial \beta} dy + \int_0^{\bar{y}} \int_{\tilde{\phi}(y,\alpha,\beta,G)}^{\bar{\phi}} \frac{\partial h^D(y-\alpha,\beta)}{\partial \beta} f(y,\phi) d\phi dy \right] \frac{\int_0^{\bar{y}} f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial G} dy}{\int_0^{\bar{y}} f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial \beta} dy} - \int_0^{\bar{y}} h^D(y-\alpha,\beta) f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial G} dy. \tag{A11}$$

Noting that $\frac{\partial \tilde{\phi}}{\partial G} < 0$, the last term is the increase in housing demand from new people pulled into the city from the increase in G. Similarly noting that $\frac{\partial \tilde{\phi}}{\partial \beta} > 0$, the first term in the square brackets is the decrease in housing demand from people pulled out of the city from the increase in β. The second term in square brackets is the decrease in existing residents' housing demand from the increase in β. To get the combined effect of G and β, the entire price effect from β in square brackets is adjusted by the rate of $\frac{d\beta}{dG}|L$.

We can get additional intuition by dividing through by $-\int_0^{\bar{y}} f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial G} dy$. Then the previous equation can be re-arranged as follows:

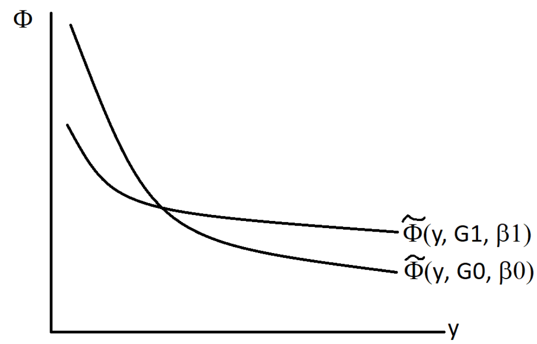


Figure A2

$$\frac{dH^D}{dG} = \frac{\int_0^{\bar{y}} \int_{\tilde{\phi}(y,\alpha,\beta,G)}^{\bar{\phi}} \frac{\partial h^D(y-\alpha,\beta)}{\partial \beta} f(y,\phi) d\phi dy}{\int_0^{\bar{y}} f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial \beta} dy} + \frac{\int_0^{\bar{y}} h^D(y-\alpha,\beta) f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial G} dy}{\int_0^{\bar{y}} f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial G} dy} - \frac{\int_0^{\bar{y}} h^D(y-\alpha,\beta) f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial \beta} dy}{\int_0^{\bar{y}} f(y,\tilde{\phi}) \frac{\partial \tilde{\phi}}{\partial \beta} dy}. \tag{A12}$$

In the above equation, the first line can be considered the "price effect on housing demand," which is clearly negative. The second line can be considered the "sorting effect." It is the average housing demand from the people pulled in by the increase in G relative to that for those pulled out by the increase in β. When there is sorting on a single dimension, this entire second line is zero because the set of people must remain the same. In general, its sign is ambiguous.

Figure A2 depicts the sorting effect. It shows two loci of $\{y, \phi\}$ describing the set of households who are indifferent about where to locate, one in the baseline at $\{G^0, \beta^0\}$ and another at the new $\{G^1, \beta^1\}$. To meet condition 5, the measure of people above both loci must be the same. However, even though $\beta^1 > \beta^0$ that does not mean the aggregate housing demand is lower, because income may have increased.

If the entire expression does remain negative, as in the case of sorting on a single dimension, then the increase in β that leaves L binding results in excess supply of housing. Thus, when G increases, there must be an equilibrating increase in α. The logic of the proof from the previous subsection applies.

We speculate that, in practice, it would be very unlikely for the sorting effect to dominate the price effect. Because housing is a normal good, we would need a combined increase of G and β that results in a richer population and for that income effect to dominate the price effect. We conclude that it is "likely" that an increase in G results in an increase in α in equilibrium, but not guaranteed. Nevertheless, empirical work should allow for the possibility.

A.4 Simulations

This appendix illustrates the model's intuition with numerical policy simulations. We consider a city with two neighborhoods, each with land area fixed at 3,333 and with $G_1 = 1$ and $G_2 = 1.5$. An outside option is available with a fixed land price at \$15,000 per unit and $G_0 = 0$. We simulate 10,000 households i with utility function,

$$u_i = (1 - \theta_i)\ln(k) + \theta_i \ln(h - \underline{h}) + \phi_i G, \tag{A13}$$

with heterogeneity in household utility according to preference parameters index by i. Substituting the budget constraint and price function for z yields the indirect utility functions

$$v_i = \max_{n,h_n} \, (1 - \theta_i)\ln(y_i - \alpha_n - \beta_n h_n) + \theta_i \ln(h_n - \underline{h}) + \phi_i G_n. \tag{A14}$$

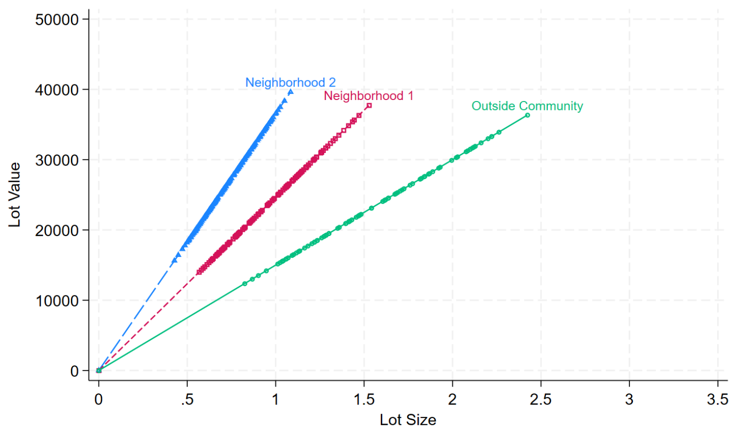
In our simulations, we allow heterogeneity in income and tastes, with income $y_i \sim$ u(40000, 100,000), housing taste parameter $\theta_i \sim$ u(0.25, 0.35), Stone-Geary housing subsistence parameter $\underline{h} = 0.2$, and $\phi_i \sim$ u(0.1, 0.5).

We consider two different land-use scenarios. In the first scenario, there are no restrictions. In the second, we introduce a restriction on the maximum number of lots at 3,643). Table A1 summarizes the outcomes for the two scenarios.

Table A1 shows that, in Scenario 1, 80 percent of households sort into the city, with over half of them living in the high-G neighborhood. With higher demand, the price of land is about 50% higher in Neighborhood 2 than Neighborhood 1. (Of course, there are no tickets.) The table also shows that richer households and households with higher tastes for public goods sort into the high-G neighborhood, as we would expect. Nevertheless, because of higher land prices, the average lot size is about 25 percent lower in Neighborhood 2. Figure A3 depicts the pricing function. The horizontal axis indicates the size of the lot and the vertical axis indicates its value. The dots represent the lower and upper bounds of the support over h in each community, plus a 1-in-20 sample of lots in between. As discussed in the main body of the paper, with no tickets, the consensus view of hedonic pricing emerges, with prices increasing proportionately from higher G.

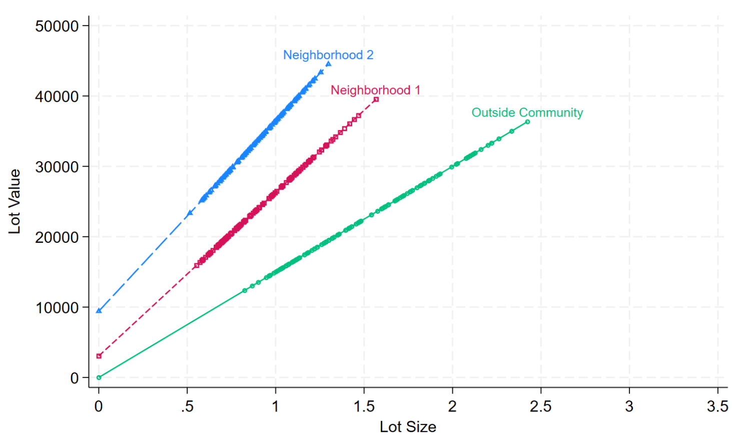
In Scenario 2, we see the introduction of tickets, as the extensive margin price is now

Figure A3: Simulation 1: No Land-Use Controls



NOTES: The figure plots housing values to lot size for the simulated equilibrium under no land-use restrictions. Each point represents a housing unit, and lines are drawn for each community, extending through the vertical axis for visual reference.

Figure A4: Simulation 2: Maximum Number of Lots



NOTES: The figure plots housing values to lot size for the simulated equilibrium under a restriction on the quantity of units in each neighborhood. Each point represents a housing unit, and lines are drawn for each community, extending through the vertical axis for visual reference.

Table A1: Results from Simulations

Attribute	Neighborhood	Scenario 1	Scenario 2
Housing Units	1	3,415	3,643
	2	4,585	3,643
Avg Lot Size	1	0.098	0.091
	2	0.073	0.091
Price of Land	1	24,694	23,277
	2	36,545	27,043
Price of Ticket	1	0	3,052
	2	0	9,418
Mean Income	1	67,967	63,267
	2	72,492	79,601
Mean ϕ	1	0.2528	0.3020
	2	0.4044	0.4041

NOTES: The table displays output from the equilibrium obtained numerically in simulations as described in the text. An outside option has low G; neighborhood 1 has medium G; and neighborhood 2 has high G. Scenario 1 involves no land use restrictions. Scenario 2 restricts supply in neighborhoods 1 and 2 to 3,643 housing units.

necessary to satisfy the condition on the number of lots in additional to equimarginality. The ticket is over three times higher in Neighborhood 2 than Neighborhood 1. At these parameters, we also see land prices falling and the difference between prices in the two neighborhoods collapsing, but in general, this will depend on preferences and incomes of the households in the economy. Figure A4 depicts the pricing function. Tickets emerge, and moreover they are increasing in G. We have found these results to hold qualitatively over a large range of parameters and alternative functional forms.

B Data and Summary Statistics

This appendix provides additional details on the data. As noted in the main text, our final sample contains 1.7 million transactions in 23,707 neighborhoods in 141 metropolitan areas (CBSAs). If, after dropping observations as described in the main text, any neighborhood has fewer than 30 transactions, we group it into a "residual neighborhood." Because these are artificial places, they are excluded from regressions that require amenity data.

Table B1 displays the cities in our sample, the number of sub-markets we break them into when estimating hedonic models of housing services, the number of unique properties for each city, the number of transactions (including repeat sales), the average price, and the number of neighborhoods (elementary school attendance zones). The total number of neighborhoods are broken out by those attendance zones for which we can match properties using observed attendance boundaries ("AB") and those to which we match properties to the nearest elementary school within the observed school district ("distance").

Table B2 reports the mean and standard deviation of amenities, by city. The amenities include fourth grade test scores,[15] distance to the CBD, the number of NPL sites, and the number of days exceeding safe thresholds of ozone.

Table B3 provides summary statistics on the regulations and redevelopment frictions in our data, by city. It displays the average WRI index by metropolitan area, the share of legacy housing that may be "locked in" in the metro area, the number of municipalities in the metro area with separate WRI data available, and the number of neighborhoods in the covered municipalities.

Finally, Table B4 summarizes the data in our application to school quality using a boundary discontinuity design. It shows the number of schools and boundaries, by city; the number of transactions and unique properties; and the normalized measure of school quality (in standard deviations).

[15] For schools with small numbers of students taking such exams, the passing proficiency data are reported in intervals. We limit the sample to schools with intervals under 20 percentage points and use the midpoint.

Table B1: Summary of Data in First Stage Capitalization Function Regressions

City	Submarkets	Properties	Transactions	Mean	Neighborhoods		
				Price	Total	AB	Distance
				($ 1000)			
Akron (OH)	1	45,555	72,054	105.9	145	43	102
Albany (NY)	1	56,390	69,744	176.3	185	27	158
Albuquerque (NM)	1	54,886	70,254	197.8	130	87	43
Allentown (PA)	1	44,518	53,040	171.4	164	5	159
Ann Arbor (MI)	1	4,474	5,946	208.6	41		41
Asheville (NC)	1	30,928	40,232	221.7	70	21	49
Atlanta (GA)	10	425,952	657,399	187.4	749	441	308
Augusta (GA)	1	31,758	44,352	167.7	93	53	40
Austin (TX)	1	43,685	62,023	206.8	267	129	138
Bakersfield (CA)	1	70,213	123,643	146.6	149	120	29
Baltimore (MD)	4	168,129	225,859	244.1	381	368	13
Baton Rouge (LA)	1	15,952	21,997	236.2	36	32	4
Bend (OR)	1	15,755	24,684	222.2	21	21	
Birmingham (AL)	1	37,947	64,139	148.1	182	28	154
Boise City (ID)	1	52,043	71,665	175.8	129	61	68
Boston (MA)	7	222,796	283,569	375.6	1014	23	991
Boulder (CO)	1	24,212	31,144	393.6	41	40	1
Bradenton (FL)	1	65,832	89,880	165.0	50	50	
Bridgeport (CT)	1	49,656	59,155	586.2	207	3	204
Buffalo (NY)	1	83,796	105,468	113.7	228	12	216
Canton (OH)	1	31,785	46,910	89.4	105	6	99
Cape Coral (FL)	1	90,806	136,621	151.1	3	3	

Continued on next page

Table B1: Summary of Data in First Stage Capitalization Function Regressions

City	Submarkets	Properties	Transactions	Mean	Neighborhoods		
				Price	Total	AB	Distance
				($ 1000)			
Charleston (WV)	1	1,556	1,727	137.9	12		12
Charleston (SC)	1	50,035	66,642	255.4	72	67	5
Charlotte (NC)	2	176,919	252,779	213.2	179	160	19
Chattanooga (TN)	1	7,303	9,972	104.5	47	1	46
Chicago (Cook) (IL)	6	193,148	251,164	244.1	948	390	558
Chicagoland (IL)	6	186,612	257,837	236.7	942	96	846
Chico (CA)	1	14,567	22,192	185.6	45	12	33
Cincinnati (OH)	2	75,028	105,658	138.8	310	49	261
Cleveland (OH)	2	146,709	210,372	109.6	464	21	443
Colorado Springs (CO)	1	45,178	62,296	258.9	155	37	118
Columbia (SC)	1	43,959	60,330	141.6	135	42	93
Columbus (OH)	2	98,981	153,564	129.9	367	78	289
Corpus Christi (TX)	1	21,874	28,203	158.4	82	43	39
Corvallis (OR)	1	5,884	7,414	255.4	12	12	
Dallas (TX)	5	419,393	586,941	204.6	1256	620	636
Dayton (OH)	1	22,916	31,109	108.5	138	13	125
Deltona (FL)	1	41,713	55,905	158.0	45	45	
Denver (CO)	4	202,310	284,325	259.9	444	320	124
Des Moines (IA)	1	39,929	66,422	150.1	130	40	90
Detroit (MI)	5	146,669	237,597	114.0	904	116	788
Dover (DE)	1	4,228	6,790	223.2	17	17	
Duluth (MN)	1	12,263	15,626	135.0	31	25	6

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Table B1: Summary of Data in First Stage Capitalization Function Regressions

City	Submarkets	Properties	Transactions	Mean	Neighborhoods		
				Price	Total	AB	Distance
				($ 1000)			
Durham (NC)	1	31,643	41,895	199.9	76	23	53
El Paso (TX)	1	22,425	26,982	139.1	130	106	24
Eugene (OR)	1	20,807	28,117	221.3	60	59	1
Fayetteville (NC)	1	29,004	38,861	133.7	59	47	12
Fort Wayne (IN)	1	23,225	41,955	117.1	80	32	48
Fresno (CA)	1	58,168	99,405	184.4	207	110	97
Gainesville (FL)	1	11,678	14,893	165.6	25	21	4
Grand Junction (CO)	1	10,291	17,126	211.1	24	22	2
Grand Rapids (MI)	1	14,084	30,213	73.0	76	4	72
Greensboro (NC)	1	56,051	74,573	147.3	129	65	64
Greenville (SC)	1	36,490	50,278	145.3	73	48	25
Harrisburg (PA)	1	17,490	21,705	127.0	98	8	90
Hartford (CT)	1	71,800	85,859	239.7	200	141	59
Hickory (NC)	1	20,550	28,076	128.1	105		105
Houston (TX)	8	144,515	554,714	208.1	711	711	
Huntsville (AL)	1	28,673	37,380	188.2	62	25	37
Indianapolis (IN)	2	83,090	168,298	139.3	335	47	288
Jackson (MS)	1	2,927	3,346	172.9	18	1	17
Jacksonville (FL)	1	98,293	134,680	234.5	169	142	27
Kansas City (MO)	3	103,819	137,952	162.1	352	352	
Knoxville (TN)	1	50,624	74,174	158.9	106	47	59
Lakeland (FL)	1	3,901	73,005	105.9	64	64	

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Table B1: Summary of Data in First Stage Capitalization Function Regressions

City	Submarkets	Properties	Transactions	Mean	Neighborhoods		
				Price	Total	AB	Distance
				($ 1000)			
Lancaster (PA)	1	32,905	40,277	176.2	112	1	111
Lansing (MI)	1	11,460	21,100	86.4	95	5	90
Las Cruces (NM)	1	5,560	6,898	194.3	26	22	4
Las Vegas (NV)	3	183,623	344,082	168.9	186	186	
Lexington (KY)	1	14,970	18,256	168.9	39	32	7
Lincoln (NE)	1	26,200	34,102	158.2	54	39	15
Little Rock (AR)	1	54,526	71,811	149.0	152	31	121
Los Angeles (LAC) (CA)	6	393,984	650,759	426.6	1353	699	654
Los Angeles (OC) (CA)	3	130,147	191,238	593.3	417	213	204
Louisville (KY)	1	11,532	14,401	120.1	83	3	80
Madison (WI)	1	16,247	20,562	240.2	36	26	10
Manchester (NH)	1	20,158	26,635	229.7	90	3	87
McAllen (TX)	1	21,851	31,467	113.5	162	90	72
Medford (OR)	1	15,329	22,688	203.6	31	31	
Memphis (TN)	1	75,674	114,345	152.8	167	143	24
Miami (FL)	6	392,135	578,009	231.6	649	249	400
Milwaukee (WI)	1	53,223	71,596	132.0	137	137	
Minneapolis (MN)	5	117,566	263,808	218.6	323	323	
Mobile (AL)	1	36,428	55,651	136.8	54	49	5
Myrtle Beach (SC)	1	20,454	28,456	202.5	22	22	
Naples (FL)	1	24,241	33,107	353.1	29	29	
Nashville (TN)	3	160,981	238,373	191.6	298	91	207

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Table B1: Summary of Data in First Stage Capitalization Function Regressions

City	Submarkets	Properties	Transactions	Mean Price	Neighborhoods Total	AB	Distance
				($ 1000)			
New Haven (CT)	1	44,091	53,553	246.2	209	11	198
New York City (NY)	2	126,520	148,607	520.5	538	38	500
New York City (NJ)	6	247,922	298,873	381.8	1256	126	1130
New London (CT)	1	15,249	18,160	239.3	83	2	81
Ocala (FL)	1	39,331	51,787	106.2	29	29	
Ogden (UT)	1	34,079	48,260	207.1	113	84	29
Oklahoma City (OK)	1	103,631	140,004	150.8	305	85	220
Omaha (NE)	1	71,894	98,891	170.5	188	80	108
Orlando (FL)	2	168,020	233,568	178.2	202	200	2
Ventura (CA)	1	46,934	72,660	456.6	173	17	156
Melbourne (FL)	1	56,833	74,126	127.3	53	53	
Panama City (FL)	1	15,182	19,560	154.6	19	19	
Pensacola (FL)	1	31,441	40,512	156.0	45	45	
Philadelphia (PA)	8	334,220	412,286	216.9	851	492	359
Phoenix (AZ)	7	337,627	590,264	184.3	572	388	184
Pittsburgh (PA)	3	101,225	118,314	133.2	326	58	268
Portland (ME)	1	4,932	5,303	258.0	32	6	26
Portland (OR)	3	122,128	166,791	261.5	354	307	47
Port St. Lucie (FL)	1	35,750	66,827	146.9	31	3	28
Poughkeepsie (NY)	1	34,653	41,719	251.6	132	11	121
Providence (RI)	1	67,038	90,639	227.0	333	2	331
Provo-Orem (UT)	1	32,301	45,961	241.7	99	75	24

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Table B1: Summary of Data in First Stage Capitalization Function Regressions

City	Submarkets	Properties	Transactions	Mean Price	Neighborhoods Total	AB	Distance
				($ 1000)			
Racine (WI)	1	6,745	9,110	96.6	14	14	
Raleigh (NC)	1	109,787	144,351	212.5	138	123	15
Reno (NV)	1	40,734	64,492	225.3	66	62	4
Richmond (VA)	1	89,320	125,431	226.9	187	116	71
Riverside (CA)	9	367,240	681,867	220.3	657	410	247
Roanoke (VA)	1	19,107	25,385	164.3	60	16	44
Rochester (NY)	1	83,443	106,352	120.5	163	31	132
Sacramento (CA)	3	177,616	304,518	257.2	367	148	219
St. Louis (MO)	5	196,386	285,940	162.1	595	44	551
Salem (OR)	1	25,153	35,058	183.4	73	69	4
Salt Lake City (UT)	1	61,554	89,287	251.1	175	122	53
San Antonio (TX)	2	100,339	139,581	178.1	375	173	202
San Diego (CA)	4	166,834	260,342	438.5	456	221	235
San Francisco (CA)	9	236,767	364,334	500.1	717	187	530
San Jose (CA)	1	61,293	88,035	628.8	296	39	257
Savannah (GA)	1	21,746	29,442	197.2	51	30	21
Scranton (PA)	1	2,992	3,567	103.7	37	2	35
Seattle (WA)	6	223,780	348,515	336.3	757	177	580
South Bend (IN)	1	13,246	20,692	114.1	67		67
Springfield (MA)	1	42,324	56,028	181.8	200	7	193
Stockton (CA)	1	59,122	112,839	176.3	120	57	63
Syracuse (NY)	1	45,699	55,481	118.0	160	17	143

Continued on next page

Table B1: Summary of Data in First Stage Capitalization Function Regressions

City	Submarkets	Properties	Transactions	Mean	Neighborhoods		
				Price	Total	AB	Distance
				($ 1000)			
Tampa-St. Pete. (FL)	5	215,850	301,422	167.2	247	247	
Toledo (OH)	1	36,516	51,996	96.3	154	15	139
Tucson (AZ)	1	69,553	106,660	237.6	131	129	2
Tulsa (OK)	1	63,521	83,011	143.3	170	73	97
Norfolk (VA)	3	91,452	126,901	229.6	210	198	12
Visalia (CA)	1	30,790	49,238	159.1	124	26	98
Washington (DC)	10	309,330	453,002	372.0	745	719	26
Wichita (KS)	1	21,603	25,685	132.8	143	65	78
Wilmington (NC)	1	32,095	43,371	246.0	46	31	15
Winston (NC)	1	29,041	39,396	148.4	78	40	38
Worcester (MA)	1	46,607	62,344	222.8	202	39	163
Youngstown (OH)	1	28,647	39,909	75.1	101	16	85
Totals		11,580,217	17,365,998		32,824	14,070	18,754

Source: Authors' calculations using housing and school attendance area data as described in Section 3.

Table B2: Summary of Amenity Data in Second Stage Ticket-and-Slope Regressions

City	Test Score (%)		CBD Distance (mi)		NPL Sites (in 5k)		Ozone Days (2009)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Akron (OH)	76.4	16.4	8.4	5.3	0.02	0.10	0.00	0.02
Albany (NY)	86.1	11.2	14.9	11.5	0.08	0.24	0.37	0.30
Albuquerque (NM)	48.5	17.7	10.5	8.0	0.10	0.30	0.00	0.00
Allentown (PA)	83.0	10.6	12.9	10.2	0.12	0.29	0.10	0.26
Ann Arbor (MI)	93.4	5.6	4.0	3.1	0.00	0.00	0.19	0.07
Asheville (NC)	86.7	6.8	14.3	8.1	0.08	0.21	0.00	0.00
Atlanta (GA)	77.0	14.6	23.9	12.9	0.00	0.00	3.05	1.24
Augusta (GA)	71.3	18.3	12.6	8.2	0.09	0.27	0.00	0.00
Austin (TX)	87.6	8.9	16.2	9.3	0.00	0.00	1.97	0.52
Bakersfield (CA)	58.3	15.1	20.9	22.4	0.03	0.16	36.81	12.68
Baltimore (MD)	90.7	8.1	12.6	9.2	0.05	0.18	0.97	1.28
Baton Rouge (LA)	56.5	15.2	9.2	3.1	0.00	0.00	5.07	1.67
Bend (OR)	86.7	5.6	9.6	8.1	0.00	0.00	0.42	0.24
Birmingham (AL)	78.6	12.0	11.2	10.1	0.00	0.04	0.79	0.37
Boise City (ID)	82.8	10.2	14.5	9.0	0.00	0.00	0.00	0.00
Boston (MA)	53.4	19.9	18.3	13.6	0.11	0.30	1.52	0.65
Boulder (CO)	91.9	7.9	9.8	4.9	0.01	0.02	2.70	0.42
Bradenton (FL)	73.1	13.1	8.4	8.7	0.00	0.00	0.64	0.38
Bridgeport (CT)	84.6	16.6	7.7	6.5	0.07	0.24	2.06	0.39
Buffalo (NY)	83.2	16.8	10.8	7.4	0.03	0.16	1.00	0.02
Canton (OH)	79.1	15.0	6.7	5.7	0.04	0.16	0.00	0.00
Cape Coral (FL)	72.0	15.0	11.4	6.2	0.00	0.00	0.00	0.00
Charleston (WV)	49.3	13.6	8.8	2.9	0.00	0.01	0.00	0.00

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Table B2: Summary of Amenity Data in Second Stage Ticket-and-Slope Regressions

City	Test Score (%)		CBD Distance (mi)		NPL Sites (in 5k)		Ozone Days (2009)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Charleston (SC)	86.9	9.6	16.3	11.9	0.06	0.22	0.00	0.00
Charlotte (NC)	81.7	12.4	14.9	10.4	0.05	0.21	1.63	0.56
Chattanooga (TN)	67.2	24.8	15.5	6.5	0.02	0.09	1.16	0.14
Chicago (Cook) (IL)	80.8	14.1	13.8	7.4	0.00	0.05	0.11	0.18
Chicagoland (IL)	86.8	11.1	33.7	10.5	0.10	0.39	0.37	0.43
Chico (CA)	56.5	14.3	15.8	8.8	0.05	0.16	6.01	3.01
Cincinnati (OH)	75.8	16.3	16.2	10.8	0.05	0.20	1.67	1.03
Cleveland (OH)	74.0	20.4	15.0	9.4	0.00	0.00	0.52	0.62
Colorado Springs (CO)	92.7	6.4	8.5	5.3	0.00	0.00	0.25	0.11
Columbia (SC)	84.0	10.6	14.9	10.7	0.02	0.13	0.00	0.03
Columbus (OH)	76.0	18.6	13.8	9.6	0.00	0.00	0.28	0.21
Corpus Christi (TX)	85.2	10.4	10.6	7.1	0.02	0.13	0.06	0.05
Corvallis (OR)	84.9	10.8	6.7	6.7	0.02	0.05	0.55	0.24
Dallas (TX)	87.7	9.6	17.3	10.4	0.02	0.11	7.75	3.89
Dayton (OH)	75.0	19.6	10.6	7.1	0.30	0.59	0.96	0.81
Deltona (FL)	73.2	10.1	14.5	9.0	0.01	0.04	0.00	0.00
Denver (CO)	89.2	9.6	11.9	9.0	0.08	0.25	1.29	0.69
Des Moines (IA)	77.8	13.7	9.9	6.8	0.09	0.27	0.00	0.00
Detroit (MI)	90.8	9.7	19.6	10.6	0.03	0.17	0.73	0.41
Dover (DE)	80.0	8.9	6.6	5.2	0.27	0.34	0.26	0.22
Duluth (MN)	74.1	12.8	33.9	29.8	0.03	0.13	0.00	0.00
Durham (NC)	80.1	12.7	14.4	10.3	0.00	0.01	0.00	0.00
El Paso (TX)	88.6	6.9	10.2	4.8	0.00	0.00	0.76	0.72

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Table B2: Summary of Amenity Data in Second Stage Ticket-and-Slope Regressions

City	Test Score (%)		CBD Distance (mi)		NPL Sites (in 5k)		Ozone Days (2009)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Eugene (OR)	80.4	8.9	10.3	10.2	0.00	0.00	0.09	0.06
Fayetteville (NC)	78.2	10.9	9.2	6.0	0.06	0.18	0.58	0.17
Fort Wayne (IN)	71.0	16.2	8.8	6.6	0.05	0.17	0.00	0.00
Fresno (CA)	67.2	16.0	12.9	11.8	0.09	0.27	39.11	8.14
Gainesville (FL)	73.3	16.0	10.7	10.4	0.14	0.29	0.00	0.00
Grand Junction (CO)	90.3	7.1	7.3	7.8	0.00	0.00	0.03	0.07
Grand Rapids (MI)	85.2	10.7	8.6	11.9	0.42	0.53	1.08	0.23
Greensboro (NC)	81.2	10.5	12.2	9.3	0.00	0.00	0.20	0.25
Greenville (SC)	86.3	7.6	11.0	6.8	0.13	0.29	0.00	0.00
Harrisburg (PA)	77.7	19.4	9.7	8.4	0.05	0.20	0.03	0.05
Hartford (CT)	86.4	13.4	13.0	7.7	0.06	0.22	1.37	0.60
Hickory (NC)	86.9	7.3	9.1	5.3	0.00	0.00	0.05	0.20
Houston (TX)	89.2	8.1	18.4	10.9	0.10	0.34	4.79	0.97
Huntsville (AL)	80.4	14.1	8.3	4.3	0.00	0.00	0.68	0.11
Indianapolis (IN)	76.2	15.0	14.0	8.7	0.02	0.13	0.65	0.51
Jackson (MS)	64.3	22.7	18.5	8.5	0.05	0.21	0.87	0.13
Jacksonville (FL)	73.5	14.0	14.1	10.1	0.10	0.29	0.40	0.17
Kansas City (MO)	67.1	24.3	15.0	9.8	0.04	0.16	0.85	0.45
Knoxville (TN)	35.5	15.4	13.6	7.5	0.01	0.06	0.99	0.36
Lakeland (FL)	66.6	9.9	12.6	8.4	0.05	0.13	0.01	0.03
Lancaster (PA)	83.1	11.0	8.5	5.6	0.05	0.19	0.72	0.22
Lansing (MI)	91.3	9.1	6.4	5.9	0.23	0.60	0.03	0.06
Las Cruces (NM)	44.8	11.2	7.8	10.2	0.28	0.39	0.01	0.05

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Table B2: Summary of Amenity Data in Second Stage Ticket-and-Slope Regressions

City	Test Score (%)		CBD Distance (mi)		NPL Sites (in 5k)		Ozone Days (2009)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Las Vegas (NV)	65.3	13.2	8.8	10.1	0.00	0.00	0.75	0.50
Lexington (KY)	79.0	12.3	5.5	4.2	0.00	0.00	0.00	0.00
Lincoln (NE)	95.9	2.5	6.8	6.1	0.00	0.00	0.00	0.00
Little Rock (AR)	76.3	17.1	15.4	10.1	0.03	0.15	1.35	0.09
Los Angeles (LAC) (CA)	67.1	16.0	15.8	9.1	0.17	0.45	11.89	13.75
Los Angeles (OC) (CA)	74.1	13.9	30.4	9.1	0.02	0.12	3.46	3.78
Louisville (KY)	75.2	10.4	15.0	10.4	0.00	0.00	0.34	0.58
Madison (WI)	76.9	11.4	5.2	1.8	0.02	0.06	0.00	0.00
Manchester (NH)	70.4	14.2	11.7	7.8	0.08	0.23	0.09	0.11
McAllen (TX)	86.1	9.2	8.8	4.9	0.00	0.00	0.00	0.00
Medford (OR)	74.5	10.4	8.1	7.5	0.00	0.00	0.00	0.00
Memphis (TN)	30.0	22.2	13.2	9.7	0.07	0.23	0.79	0.18
Miami (FL)	73.6	13.6	21.1	16.0	0.11	0.27	0.01	0.05
Milwaukee (WI)	67.7	21.1	7.9	5.7	0.04	0.19	1.09	0.58
Minneapolis (MN)	75.4	15.1	15.0	8.4	0.15	0.43	0.00	0.00
Mobile (AL)	86.3	10.1	11.1	7.2	0.05	0.20	0.88	0.44
Myrtle Beach (SC)	89.2	6.0	13.6	7.6	0.00	0.00	0.11	0.13
Naples (FL)	70.1	12.7	12.3	9.3	0.00	0.00	0.00	0.00
Nashville (TN)	35.8	17.3	22.8	13.2	0.00	0.00	0.28	0.22
New Haven (CT)	81.0	13.8	10.0	6.3	0.10	0.27	0.77	0.40
New York City (NY)	91.8	8.3	27.3	12.4	0.32	0.64	1.76	0.87
New York City (NJ)	78.5	16.2	24.1	13.7	0.32	0.62	1.29	0.55
New London (CT)	84.4	11.9	9.8	5.0	0.02	0.10	0.81	0.20

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Table B2: Summary of Amenity Data in Second Stage Ticket-and-Slope Regressions

City	Test Score (%)		CBD Distance (mi)		NPL Sites (in 5k)		Ozone Days (2009)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Ocala (FL)	75.2	8.3	9.1	5.9	0.00	0.00	0.02	0.05
Ogden (UT)	69.1	14.8	9.3	7.4	0.23	0.57	0.36	0.19
Oklahoma City (OK)	66.5	16.4	14.0	10.4	0.01	0.07	1.12	1.13
Omaha (NE)	94.0	5.3	11.8	9.1	0.03	0.14	0.00	0.00
Orlando (FL)	73.4	13.1	12.4	8.2	0.05	0.17	0.10	0.18
Ventura (CA)	67.4	16.5	12.9	8.9	0.08	0.26	7.29	6.26
Melbourne (FL)	79.4	11.3	19.7	14.0	0.04	0.15	0.00	0.00
Panama City (FL)	73.7	13.0	7.3	5.1	0.00	0.00	0.82	0.12
Pensacola (FL)	72.6	15.3	10.8	8.4	0.20	0.44	1.34	0.19
Philadelphia (PA)	78.4	18.1	16.1	12.0	0.29	0.53	0.66	0.57
Phoenix (AZ)	63.9	15.9	18.1	13.0	0.02	0.13	0.53	0.50
Pittsburgh (PA)	84.1	13.7	14.1	10.5	0.03	0.19	0.70	1.01
Portland (ME)	70.6	13.6	30.9	13.0	0.09	0.24	0.99	0.58
Portland (OR)	75.3	16.8	12.7	8.4	0.10	0.36	0.79	0.31
Port St. Lucie (FL)	79.7	9.6	11.1	4.7	0.11	0.26	0.00	0.00
Poughkeepsie (NY)	84.0	12.9	17.4	11.2	0.12	0.28	0.83	0.42
Providence (RI)	53.7	18.8	12.1	8.6	0.21	0.48	1.03	0.44
Provo-Orem (UT)	79.4	10.0	9.2	5.9	0.00	0.00	0.29	0.21
Racine (WI)	63.8	15.2	1.8	0.8	0.00	0.00	2.78	0.16
Raleigh (NC)	86.4	7.0	12.8	8.1	0.03	0.12	0.00	0.00
Reno (NV)	70.5	14.1	6.1	4.7	0.00	0.00	0.00	0.00
Richmond (VA)	89.6	7.1	13.1	8.8	0.04	0.17	0.00	0.00
Riverside (CA)	65.4	14.2	23.3	25.4	0.05	0.19	42.91	19.18

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Table B2: Summary of Amenity Data in Second Stage Ticket-and-Slope Regressions

City	Test Score (%)		CBD Distance (mi)		NPL Sites (in 5k)		Ozone Days (2009)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Roanoke (VA)	87.0	9.8	7.3	6.0	0.00	0.00	0.00	0.00
Rochester (NY)	87.9	9.8	14.2	11.0	0.01	0.06	0.11	0.16
Sacramento (CA)	69.3	15.4	18.0	15.2	0.03	0.15	12.53	7.74
St. Louis (MO)	58.5	25.9	16.1	11.1	0.04	0.20	0.92	0.40
Salem (OR)	76.4	11.7	8.7	7.3	0.00	0.00	1.02	0.04
Salt Lake City (UT)	70.3	13.1	11.3	8.5	0.21	0.44	1.21	0.44
San Antonio (TX)	84.8	9.6	14.1	10.5	0.01	0.11	1.10	0.83
San Diego (CA)	71.2	15.7	17.4	12.3	0.00	0.00	1.79	3.03
San Francisco (CA)	69.6	19.2	14.0	9.0	0.03	0.17	0.86	1.29
San Jose (CA)	74.2	15.1	8.6	6.3	0.65	1.59	1.48	0.93
Savannah (GA)	70.8	13.4	12.2	8.4	0.00	0.00	0.00	0.00
Scranton (PA)	83.7	11.6	21.2	8.2	0.09	0.24	0.00	0.00
Seattle (WA)	58.0	18.2	20.4	11.2	0.11	0.37	0.66	0.69
South Bend (IN)	73.5	16.9	5.2	4.2	0.09	0.23	0.16	0.09
Springfield (MA)	37.7	16.3	12.4	11.5	0.00	0.03	3.11	0.73
Stockton (CA)	63.0	13.4	11.4	5.8	0.08	0.23	4.76	1.89
Syracuse (NY)	82.1	15.4	12.4	10.7	0.04	0.16	0.52	0.21
Tampa-St. Pete. (FL)	71.1	13.5	16.1	8.8	0.07	0.31	0.29	0.40
Toledo (OH)	79.0	15.1	10.8	9.5	0.00	0.00	0.28	0.30
Tucson (AZ)	60.0	18.4	9.1	10.7	0.00	0.00	0.05	0.12
Tulsa (OK)	64.3	15.7	12.4	8.6	0.01	0.05	1.84	0.55
Norfolk (VA)	87.3	8.6	12.8	11.0	0.17	0.48	0.00	0.00
Visalia (CA)	60.2	15.0	14.4	9.8	0.08	0.25	42.77	5.84

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Table B2: Summary of Amenity Data in Second Stage Ticket-and-Slope Regressions

City	Test Score (%)		CBD Distance (mi)		NPL Sites (in 5k)		Ozone Days (2009)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Washington (DC)	84.3	15.8	19.0	13.8	0.04	0.18	0.66	0.67
Wichita (KS)	85.8	10.9	12.8	10.0	0.04	0.17	1.98	0.07
Wilmington (NC)	82.8	9.5	14.4	10.6	0.02	0.06	0.09	0.09
Winston (NC)	82.6	12.2	13.1	8.7	0.01	0.09	0.35	0.15
Worcester (MA)	44.6	18.0	13.0	8.1	0.02	0.12	2.81	0.82
Youngstown (OH)	79.1	16.9	9.1	6.0	0.01	0.10	0.17	0.10

Source: Authors' calculations using housing and school attendance area data as described in Section 3.

Table B3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Property Attributes
Akron (OH)	84	0.32	0.80	2	34	0.19	yes
Albany (NY)	119	0.22	0.80				yes
Albuquerque (NM)	112	0.86	0.57	1	73	1.22	
Allentown (PA)	96	0.29	0.79	2	11	0.81	yes
Ann Arbor (MI)	24	1.30	0.72	1	18	3.42	yes
Asheville (NC)	48	-0.48	0.67	1	12	0.76	yes
Atlanta (GA)	591	0.18	0.58	15	105	0.60	
Augusta (GA)	70	-1.24	0.63	2	7	-1.03	yes
Austin (TX)	197	0.29	0.52	4	113	1.91	
Bakersfield (CA)	124	0.58	0.69				yes
Baltimore (MD)	356	1.77	0.72	3	93	-0.39	
Baton Rouge (LA)	33	-0.97	0.63				
Bend (OR)	20	1.07	0.39	1	10	0.82	yes
Birmingham (AL)	95	-0.21	0.74				yes
Boise City (ID)	95	-0.54	0.56	3	53	-0.74	yes
Boston (MA)	570	2.19	0.82	15	116	0.74	yes
Boulder (CO)	39	3.92	0.55	2	6	3.62	yes
Bradenton (FL)	49	1.41	0.50	2	6	1.76	yes
Bridgeport (CT)	130	0.39	0.83				yes
Buffalo (NY)	128	-0.35	0.87	3	40	-1.17	yes
Canton (OH)	62	-0.98	0.77				yes
Cape Coral (FL)	2	-0.06	0.39				yes
Charleston (WV)	7	-1.44	0.79				yes

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Table B3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Property Attributes
Charleston (SC)	60	-0.99	0.59	2	16	-0.70	yes
Charlotte (NC)	170	-0.40	0.69	1	66	-0.97	yes
Chattanooga (TN)	22	-1.03	0.66				
Chicago (Cook) (IL)	690	-0.24	0.87				yes
Chicagoland (IL)	602	0.52	0.68	18	110	-0.18	yes
Chico (CA)	25	1.42	0.63				yes
Cincinnati (OH)	165	-0.53	0.75	6	40	-0.60	yes
Cleveland (OH)	232	-0.05	0.82	15	121	-0.54	yes
Colorado Springs (CO)	105	1.10	0.58	1	70	0.37	
Columbia (SC)	88	-0.80	0.61	2	17	-0.53	
Columbus (OH)	231	0.30	0.74	6	113	0.50	yes
Corpus Christi (TX)	55	-0.40	0.70	1	39	-0.89	
Corvallis (OR)	10	0.60	0.63	2	8	0.24	yes
Dallas (TX)	951	-0.31	0.60	31	594	-0.19	yes
Dayton (OH)	87	-0.52	0.79	4	27	-1.50	yes
Deltona (FL)	44	0.72	0.55	2	5	0.78	
Denver (CO)	373	1.36	0.54	8	193	1.25	yes
Des Moines (IA)	89	-1.04	0.74				yes
Detroit (MI)	529	0.35	0.79	20	230	0.09	
Dover (DE)	17	1.22	0.67				yes
Duluth (MN)	21	-0.43	0.81				yes
Durham (NC)	51	0.92	0.67	2	24	1.41	yes
El Paso (TX)	114	1.00	0.65	1	96	0.57	yes

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Table B3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Property Attributes
Eugene (OR)	42	0.64	0.63				yes
Fayetteville (NC)	51	-0.65	0.61	2	22	-1.15	yes
Fort Wayne (IN)	59	-1.03	0.77				yes
Fresno (CA)	154	1.79	0.66	4	104	1.39	yes
Gainesville (FL)	22	0.24	0.52	1	10	0.09	yes
Grand Junction (CO)	22	0.73	0.55				yes
Grand Rapids (MI)	29	0.22	0.75				yes
Greensboro (NC)	101	-0.44	0.71	4	51	-0.36	
Greenville (SC)	61	-1.12	0.67	2	5	-0.97	yes
Harrisburg (PA)	60	0.88	0.76				yes
Hartford (CT)	165	0.86	0.80				yes
Hickory (NC)	58	-0.59	0.67	2	9	-0.48	yes
Houston (TX)	706	-0.16	0.52				yes
Huntsville (AL)	45	-1.62	0.74	2	31	-1.83	
Indianapolis (IN)	216	-0.83	0.72				yes
Jackson (MS)	8	-1.21	0.61				
Jacksonville (FL)	148	0.18	0.63	1	96	1.08	yes
Kansas City (MO)	320	-1.00	0.73	12	148	-0.76	
Knoxville (TN)	75	-0.27	0.69	2	5	-0.90	
Lakeland (FL)	63	0.46	0.57				yes
Lancaster (PA)	69	0.61	0.77	5	21	0.07	yes
Lansing (MI)	49	0.79	0.75				yes
Las Vegas (NV)	182	-1.15	0.46				yes

Continued on next page

Table B3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Property Attributes
Lexington (KY)	36	0.54	0.68				yes
Lincoln (NE)	41	-0.12	0.70	1	36	0.96	yes
Little Rock (AR)	100	-1.06	0.63	3	27	-1.34	
Los Angeles (LAC) (CA)	1,113	0.89	0.85				yes
Los Angeles (OC) (CA)	370	0.70	0.61				yes
Louisville (KY)	47	-0.81	0.67	1	7	-1.26	yes
Madison (WI)	32	0.65	0.70				yes
Manchester (NH)	47	2.50	0.72	1	12	0.11	yes
McAllen (TX)	135	-0.47	0.56	6	49	-0.36	yes
Medford (OR)	26	1.33	0.62	1	12	1.05	yes
Memphis (TN)	137	1.75	0.65	2	7	1.40	yes
Miami (FL)	235	1.02	0.48	14	65	0.94	yes
Milwaukee (WI)	125	0.61	0.82	3	85	-0.89	yes
Minneapolis (MN)	317	0.61	0.68	6	24	0.41	yes
Mobile (AL)	46	-1.75	0.68	1	22	-2.34	yes
Myrtle Beach (SC)	21	-0.91	0.40				yes
Naples (FL)	28	0.67	0.33				
Nashville (TN)	201	-0.42	0.64	7	34	-0.75	yes
New Haven (CT)	132	0.20	0.82				yes
New York City (NY)	336	1.08	0.89	5	40	-0.21	yes
New York City (NJ)	777	1.31	0.84	21	182	0.05	
New London (CT)	39	0.66	0.78				yes
Ogden (UT)	96	0.18	0.63	8	60	-0.27	yes

Continued on next page

Table B3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Property Attributes
Oklahoma City (OK)	193	-0.60	0.67	6	121	-0.78	yes
Omaha (NE)	132	-0.78	0.73	1	75	0.04	yes
Orlando (FL)	200	0.69	0.55	6	50	0.46	
Ventura (CA)	123	1.83	0.60				yes
Melbourne (FL)	52	0.86	0.65	4	26	0.59	yes
Panama City (FL)	18		0.54				yes
Pensacola (FL)	42	-1.05	0.63				yes
Philadelphia (PA)	660	1.52	0.81	5	166	0.03	yes
Phoenix (AZ)	516	1.11	0.49	13	371	1.31	
Pittsburgh (PA)	186	0.23	0.87	6	46	0.46	yes
Portland (ME)	14	1.83	0.63				yes
Portland (OR)	310	0.61	0.63	14	137	0.27	yes
Poughkeepsie (NY)	84	0.26	0.77				yes
Providence (RI)	175	2.32	0.84	6	55	0.27	yes
Provo-Orem (UT)	86	0.41	0.57	5	38	-0.44	yes
Racine (WI)	13	-0.28	0.80	1	13	-1.43	yes
Raleigh (NC)	131	0.76	0.62	3	47	1.19	
Reno (NV)	61	-0.09	0.50	2	47	0.01	yes
Richmond (VA)	151	-0.43	0.65	2	7	-0.42	yes
Riverside (CA)	559	0.98	0.60	16	130	0.89	yes
Roanoke (VA)	39	-0.64	0.69	1	17	-0.67	yes
Rochester (NY)	93	-0.36	0.79				yes
Sacramento (CA)	273	0.78	0.60				yes

Continued on next page

Table B3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Property Attributes
St. Louis (MO)	323	-0.83	0.76	14	91	-1.18	yes
Salem (OR)	56	0.64	0.59	1	26	0.86	yes
Salt Lake City (UT)	138	-0.35	0.63	8	86	0.04	yes
San Antonio (TX)	276	-0.17	0.66	3	191	2.69	yes
San Diego (CA)	370	0.87	0.60				yes
San Francisco (CA)	519	1.12	0.79	16	155	1.40	yes
San Jose (CA)	225	0.40	0.68				yes
Savannah (GA)	38	-0.27	0.72	1	17	0.12	yes
Scranton (PA)	27	0.20	0.82	2	7	-0.02	
Seattle (WA)	475	1.58	0.70	18	182	1.48	yes
South Bend (IN)	39	-1.02	0.82				yes
Springfield (MA)	92	0.97	0.83	7	59	-0.13	yes
Stockton (CA)	89	0.88	0.67				yes
Syracuse (NY)	99	-0.68	0.79				yes
Tampa-St. Pete. (FL)	245	-0.05	0.53	5	79	0.87	
Toledo (OH)	97	-0.76	0.77	5	54	-1.69	yes
Tucson (AZ)	121	1.91	0.53	4	85	0.40	
Tulsa (OK)	119	-0.99	0.66	2	63	-1.24	
Norfolk (VA)	196	0.20	0.66	6	151	-0.14	yes
Visalia (CA)	78	0.76	0.65				yes
Washington (DC)	694	0.51	0.67	8	83	0.63	yes
Wichita (KS)	106	-1.36	0.77	5	20	-1.24	yes
Wilmington (NC)	38	-0.93	0.55	1	12	0.26	yes

Continued on next page

Table B3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Property Attributes
Winston (NC)	57	-0.69	0.70	2	30	-0.22	yes
Worcester (MA)	98	3.13	0.82				yes
Youngstown (OH)	50	-0.23	0.81	2	6	-0.25	yes

Source: Authors' calculations using housing and school attendance area data as described in Section 3.

Table B4: Summary of Data in Hedonic School Boundary Regressions

City	Boundaries	Schools	Properties	Transactions	Score Diff SD
Akron (OH)	70	38	26,907	44,946	1.31
Albuquerque (NM)	241	87	90,254	116,192	1.16
Asheville (NC)	42	21	12,623	16,936	0.59
Atlanta (GA)	1,286	441	574,593	866,906	0.92
Augusta (GA)	134	52	27,298	40,127	1.25
Austin (TX)	327	123	42,247	60,014	1.04
Bakersfield (CA)	284	112	105,047	187,933	1.24
Baltimore (MD)	943	350	276,679	372,174	1.16
Baton Rouge (LA)	109	33	22,129	30,342	1.07
Bend (OR)	44	21	22,354	35,421	0.59
Birmingham (AL)	55	42	14,781	26,217	1.54
Boise City (ID)	156	59	63,688	85,858	1.34
Boulder (CO)	103	40	39,459	51,091	1.04
Bradenton (FL)	135	50	91,381	126,487	1.03
Charleston (SC)	120	58	66,668	89,255	1.08
Charlotte (NC)	451	161	291,137	416,368	1.19
Chicago (Cook) (IL)	794	338	151,029	208,839	1.37
Chicagoland (IL)	205	97	26,898	51,136	0.77
Chico (CA)	26	11	11,737	16,805	1.30
Cincinnati (OH)	52	38	9,252	14,343	1.23
Cleveland (OH)	13	16	1,574	2,021	0.67
Colorado Springs (CO)	70	33	22,875	31,380	1.23
Columbia (SC)	101	42	29,079	39,582	1.45
Columbus (OH)	140	69	53,880	93,090	1.46

Continued on next page

Table B4: Summary of Data in Hedonic School Boundary Regressions

City	Boundaries	Schools	Properties	Transactions	Score Diff SD
Corpus Christi (TX)	94	42	22,588	29,580	1.23
Corvallis (OR)	20	10	8,362	10,437	0.87
Dallas (TX)	1,566	608	427,547	598,766	1.16
Deltona (FL)	123	45	63,265	85,395	1.04
Denver (CO)	851	307	308,476	432,904	1.09
Des Moines (IA)	85	42	38,742	59,683	1.13
Detroit (MI)	283	112	26,205	43,650	2.11
Dover (DE)	38	18	7,714	12,492	0.97
Duluth (MN)	33	20	11,475	14,623	1.05
Durham (NC)	59	24	34,945	48,119	1.36
El Paso (TX)	257	106	34,611	41,469	0.94
Eugene (OR)	95	41	28,360	38,548	1.02
Fayetteville (NC)	107	43	41,510	56,254	1.24
Fort Wayne (IN)	82	31	25,412	47,339	1.61
Fresno (CA)	295	108	85,694	147,260	0.90
Gainesville (FL)	55	21	15,510	19,651	1.32
Grand Junction (CO)	56	22	18,255	30,730	1.28
Greensboro (NC)	171	64	68,500	90,907	1.14
Greenville (SC)	134	48	55,248	76,375	0.97
Hartford (CT)	366	140	99,661	120,445	1.00
Houston (TX)	1,763	707	247,936	1,023,433	1.02
Huntsville (AL)	55	23	19,181	25,380	1.51
Indianapolis (IN)	84	49	31,565	63,517	1.60
Jacksonville (FL)	397	142	145,164	201,864	1.17

Continued on next page

Table B4: Summary of Data in Hedonic School Boundary Regressions

City	Boundaries	Schools	Properties	Transactions	Score Diff SD
Kansas City (MO)	858	317	168,047	223,693	0.97
Knoxville (TN)	109	43	58,787	87,364	1.27
Lakeland (FL)	168	64	6,686	114,424	1.20
Las Cruces (NM)	55	22	8,208	10,299	0.90
Las Vegas (NV)	503	181	335,900	634,671	1.11
Lexington (KY)	84	32	27,333	33,494	1.17
Lincoln (NE)	87	36	39,923	51,592	1.11
Little Rock (AR)	59	30	25,899	34,597	1.71
Los Angeles (LAC) (CA)	1,801	690	423,487	704,380	1.05
Los Angeles (OC) (CA)	531	212	139,770	205,007	0.94
Madison (WI)	47	25	20,575	25,439	1.01
McAllen (TX)	251	89	25,276	36,359	1.06
Medford (OR)	61	27	22,639	33,970	1.17
Memphis (TN)	292	126	88,293	133,657	1.13
Miami (FL)	671	247	477,054	683,803	1.14
Milwaukee (WI)	277	126	76,749	104,043	1.12
Minneapolis (MN)	861	318	199,178	459,793	1.00
Mobile (AL)	128	47	54,042	82,562	1.08
Myrtle Beach (SC)	50	22	19,674	27,557	0.78
Naples (FL)	65	29	30,372	41,451	0.94
Nashville (TN)	221	88	111,450	166,025	1.14
New Haven (CT)	14	9	5,126	5,982	0.69
New York City (NY)	69	29	6,886	7,903	0.99
New York City (NJ)	236	108	26,744	40,687	1.21

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Table B4: Summary of Data in Hedonic School Boundary Regressions

City	Boundaries	Schools	Properties	Transactions	Score Diff SD
Ocala (FL)	72	28	34,623	46,104	0.90
Ogden (UT)	214	84	51,893	71,522	0.93
Oklahoma City (OK)	109	65	27,839	37,833	1.41
Omaha (NE)	141	66	50,231	68,089	2.08
Orlando (FL)	582	201	265,766	372,298	1.05
Ventura (CA)	43	17	14,828	21,103	1.14
Melbourne (FL)	126	53	82,231	108,459	1.06
Panama City (FL)	34	19	14,158	18,136	1.20
Pensacola (FL)	92	43	31,044	40,261	1.24
Philadelphia (PA)	1,458	472	439,418	544,918	1.02
Phoenix (AZ)	1,071	384	431,296	752,598	0.97
Pittsburgh (PA)	83	49	29,231	34,480	1.26
Portland (OR)	805	295	208,083	283,990	1.10
Provo-Orem (UT)	181	74	47,674	67,277	0.89
Racine (WI)	31	14	11,772	15,918	1.66
Raleigh (NC)	502	124	189,113	247,851	0.78
Reno (NV)	153	61	65,680	105,055	1.21
Richmond (VA)	293	113	125,118	179,629	1.14
Riverside (CA)	1,120	409	465,550	876,599	0.99
Roanoke (VA)	35	16	14,211	21,397	1.62
Rochester (NY)	58	29	14,100	19,693	0.89
Sacramento (CA)	392	147	181,706	324,747	1.17
St. Louis (MO)	71	41	30,836	40,513	0.71
Salem (OR)	120	55	36,935	51,653	1.29

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Table B4: Summary of Data in Hedonic School Boundary Regressions

City	Boundaries	Schools	Properties	Transactions	Score Diff SD
Salt Lake City (UT)	333	120	81,702	119,753	1.10
San Antonio (TX)	431	172	100,142	142,932	1.19
San Diego (CA)	548	218	174,416	274,861	1.10
San Francisco (CA)	451	186	164,560	272,603	1.29
San Jose (CA)	81	39	22,970	32,498	1.28
Savannah (GA)	70	30	21,976	30,065	1.09
Seattle (WA)	414	177	134,973	211,039	1.00
Stockton (CA)	125	54	72,657	140,829	1.10
Tampa-St. Pete. (FL)	666	246	366,635	516,788	1.11
Toledo (OH)	12	15	237	320	0.78
Tucson (AZ)	326	121	98,793	153,771	1.11
Tulsa (OK)	151	67	46,025	60,867	1.32
Norfolk (VA)	489	196	149,520	210,476	1.28
Visalia (CA)	62	24	26,844	43,120	1.37
Washington (DC)	1,870	683	521,112	766,507	1.22
Wichita (KS)	137	56	13,539	16,213	1.32
Wilmington (NC)	67	32	37,550	51,693	1.00
Winston (NC)	105	41	37,510	50,912	1.46
Worcester (MA)	70	32	14,286	20,280	1.23
Youngstown (OH)	17	15	533	707	0.78

Source: Authors' calculations using housing and school attendance area data as described in Section 3.

C Additional Specifications of the Hedonic Equilibrium

This appendix provides additional analyses for the models in Section 5.

C.1 First-stage results

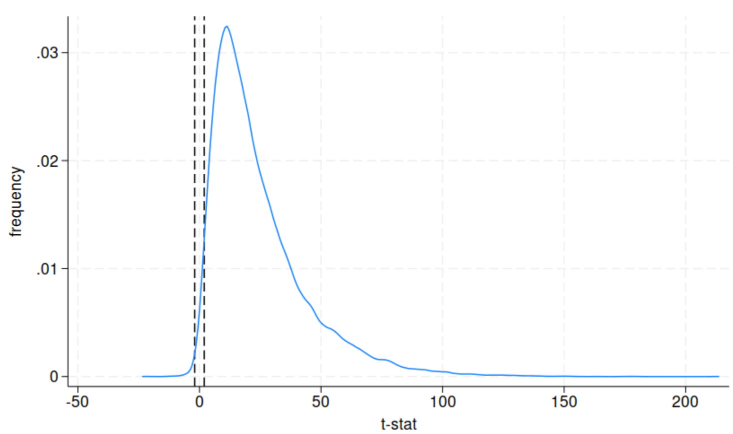
Figures C1 and C2 illustrate the distribution of t-statistics from the first stage estimates of tickets from Equation 6, with one observation per neighborhood. Figure C1 uses housing services (model i), the least complex, and Figure C2 uses housing services model (v), the most complex. In both cases, the results indicate most neighborhoods have positive and statistically significant tickets.

C.2 Additional Results on the Capitalization Function

Table C1 displays the implied amenity premium in a typical metro area, at different percentiles of the housing size distribution, in average-level and high-level zoning. It expands on the results in Table 2, in which the results were based only on housing services Model (iii), land and living area interacted with structure age. Table C1 provides results for the other models and spells out the components of the capitalization terms for each.

Regardless of the housing services index used, tickets are an important component of the gap between lower and higher amenity neighborhoods within cities. The fraction of a median-sized property's premium accounted for by tickets ranges from about two fifths to complete capitalization. And in all cases, the ticket value is higher for the more stringently

Figure C1: Distribution of Tickets from the First-Stage (Housing Services Model i)

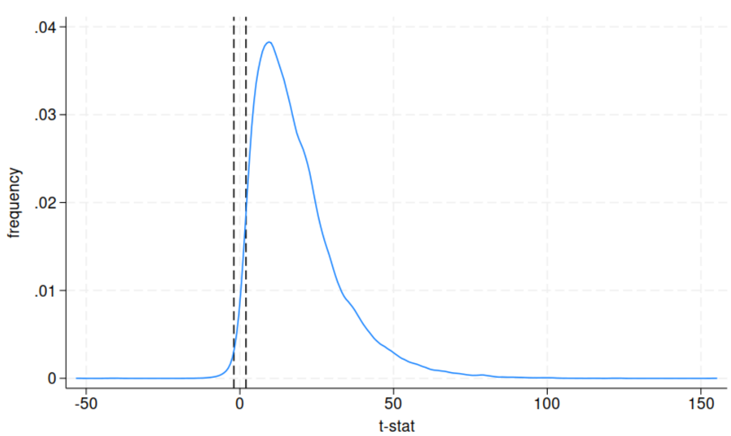


NOTES: The figure plots a kernel density of the t-statistics across neighborhoods, from Equation 6 using Housing Services Model i. The vertical lines represent the conventional large-N 95 percent confidence interval.

regulated city. Where the housing service models differ is the extent to which capitalization appears to occur in the intensive margin term (see columns 4 and 8), which is not surprising since the price per unit will naturally depend on what the substance of the "units" is. This in turn affects the fraction due to tickets vis-a-slopes mechanically, but qualitatively, the monetary value of the tickets is salient in all models.

Table C2 displays the implied amenity premium in a typical metro area for the models using housing stock age (the median of the index share developed by 1970 as of 1980) as the development friction. Again, ticket capitalization of amenities is apparent for an area of average development history. Across models, the ticket share ranges from roughly one half to full capitalization. And like *de jure* zoning, the effect of more distant historical development is to lock in the stock and increase ticket values. As with the zoning index, the differences across housing service models arise in the degree of slope capitalization, which mechanically affects ticket shares. But ticket are economically important no matter which housing service index is employed.

Figure C2: Distribution of Tickets from the First-Stage (Housing Services Model v)



NOTES: The figure plots a kernel density of the t-statistics across neighborhoods, from Equation 6 using Housing Services Model v. The vertical lines represent the conventional large-N 95 percent confidence interval.

Table C1: Capitalization Function Under Metro-Level Zoning: Additional Models

	Model	Property Size (pctile) (1)	Base Value ($ 1000) (2)	Average Zoning: Ticket ($ 1000) (3)	Average Zoning: Slope ($ 1000) (4)	Average Zoning: Premium ($ 1000) (5)	Average Zoning: Ticket Share (6)	High Zoning: Ticket ($ 1000) (7)	High Zoning: Slope ($ 1000) (8)	High Zoning: Premium ($ 1000) (9)	High Zoning: Ticket Share (10)
(i)	Land Only	25	159.7	43.9	10.7	54.6	0.80	57.6	10.8	68.4	0.84
		50	170.7	43.9	15.0	58.9	0.74	57.6	15.2	72.8	0.79
		75	193.5	43.9	25.2	69.0	0.64	57.6	25.4	83.0	0.69
(ii)	Living Area	25	128.5	19.0	17.2	36.1	0.53	22.6	23.1	45.8	0.49
		50	148.3	19.0	22.1	41.1	0.46	22.6	29.8	52.4	0.43
		75	177.9	19.0	29.2	48.2	0.39	22.6	39.5	62.1	0.36
(iii)	Land, Capital Adj.	25	60.1	31.1	6.5	37.6	0.83	42.2	8.1	50.2	0.84
		50	63.8	31.1	9.1	40.2	0.77	42.2	11.4	53.5	0.79
		75	71.5	31.1	15.2	46.3	0.67	42.2	19.0	61.2	0.69
(iv)	Land & Liv. Area	25	134.7	45.3	1.1	46.3	0.98	59.6	1.1	60.7	0.98
		50	149.2	45.3	1.5	46.7	0.97	59.6	1.5	61.1	0.98
		75	180.2	45.3	2.3	47.5	0.95	59.6	2.4	62.0	0.96
(v)	Property Attributes	25	165.1	67.0	-2.0	65.0	1.03	85.2	-2.1	83.2	1.02
		50	170.8	67.0	-3.9	63.1	1.06	85.2	-4.1	81.2	1.05
		75	190.6	67.0	-10.4	56.6	1.18	85.2	-10.8	74.4	1.15

NOTES: The table reports the housing price function at middle quartiles of the housing services distribution for a baseline (lower amenity index, 25th percentile) and prime (higher amenity index, 75th percentile) neighborhood, in a typical (mean regulation) city and a more regulated (1 s.d. higher WRI index) city. The panels correspond to different models of the housing services function.

Table C2: Capitalization Function Under Housing Stock Age Index

	Model	Property Size (pctile) (1)	Base Value ($ 1000) (2)	Average Zoning: Ticket ($ 1000) (3)	Average Zoning: Slope ($ 1000) (4)	Average Zoning: Premium ($ 1000) (5) (3)+(4)	Average Zoning: Ticket Share (6) (3) / (5)	High Zoning: Ticket ($ 1000) (7)	High Zoning: Slope ($ 1000) (8)	High Zoning: Premium ($ 1000) (9) (7)+(8)	High Zoning: Ticket Share (10) (7) / (9)
(i)	Land	25	159.7	50.2	12.7	62.9	0.80	59.3	10.2	69.5	0.85
	Only	50	170.7	50.2	17.9	68.1	0.74	59.3	14.4	73.7	0.81
		75	193.5	50.2	30.0	80.2	0.63	59.3	24.0	83.3	0.71
(ii)	Living	25	128.5	22.3	19.5	41.8	0.53	28.6	23.6	52.3	0.55
	Area	50	148.3	22.3	25.1	47.4	0.47	28.6	30.4	59.0	0.49
		75	177.9	22.3	33.2	55.5	0.40	28.6	40.3	68.9	0.42
(iii)	Land,	25	67.5	32.7	6.4	39.1	0.84	40.8	7.8	48.6	0.84
	Capital Adj.	50	71.7	32.7	8.9	41.7	0.79	40.8	11.0	51.7	0.79
		75	81.7	32.7	14.9	47.7	0.69	40.8	18.3	59.1	0.69
(iv)	Land &	25	134.7	54.9	0.5	55.4	0.99	62.1	3.5	65.6	0.95
	Liv. Area	50	149.2	54.9	0.7	55.6	0.99	62.1	4.9	67.0	0.93
		75	180.2	54.9	1.1	56.0	0.98	62.1	7.6	69.8	0.89
(v)	Property	25	165.1	77.8	-2.5	75.3	1.03	86.1	-2.1	84.0	1.02
	Attributes	50	170.8	77.8	-4.9	72.9	1.07	86.1	-4.1	82.0	1.05
		75	190.6	77.8	-13.1	64.7	1.20	86.1	-10.9	75.2	1.14

NOTES: The table reports the housing price function at middle quartiles of the housing services distribution for a baseline (lower amenity index, 25th percentile) and prime (higher amenity index, 75th percentile) neighborhood, in a typical (average fraction of stock developed by 1970) city and an older (1 s.d. higher fraction of stock developed by 1970) city. The panels correspond to different models of the housing services function.

D Implications of Using a Mis-specified Semilog Model

This appendix provides Monte Carlo analysis of the implication of using a mis-specified semilog model when the true model is given by Equation 6. Following the form of Equation (6), we draw data according to

$$p_{in} = [\alpha_c + \alpha_G G_n + exp(\beta_G G_n + H_i)] + \epsilon_{in}, \tag{D1}$$

where p is the price, α_c is an intercept, α_G is the extent of ticket capitalization of neighborhood amenity G, β_G is the slope capitalization, H is housing services, and ϵ is an error term idiosyncratic to draw i.

We consider three scenarios. In scenario 1, we set $\beta = 0$ to reflect 100 percent ticket capitalization. In scenario 2, we consider a mixed case of both ticket and slope capitalization. In scenario 3, we set $\alpha = 0$ for full slope capitalization. All scenarios fix the premium at the median-sized property.[16]

The econometrician observes H, G, and p, and estimates a regression to recover the parameters α_c, α_G, and β_G. We then evaluate the difference it makes when estimating the full model above in contrast to the commonly used semilog model:

$$\ln(p_{in}) = \tilde{\beta}_c + \tilde{\beta}_G G_n + H_i + \epsilon_{in}, \tag{D2}$$

which effectively assumes that $\alpha = 0$ and so is mis-specified in cases 2 and 3.

Figure D1 presents results from the three simulations, from full slope capitalization (left column), half slope and half ticket capitalization (center), and full ticket capitalization (right). Panel A plots the results from the two regressions (Equations D1 and D2), plotting the premium associated with the high-G neighborhood across the housing services distribution obtained from the true model and the semilog hedonic model.

In the left column, when tickets are absent, the two models come to the same result and accurately depict the premium for the high-G neighborhood. When tickets are the *only* form of capitalization, as shown in the rightmost column, the semilog model misstates capitalization in a particular way. The semilog model results from minimum distance estimation, so it can roughly recover the premium at the average level of housing services. However, it

[16] Thus, the relationship between α and β is determined by the constraint of a fixed premium at the median level of housing services. For the intermediate case, with preset premium Δ_{med} and median housing services H_{med}, the relationship is expressed as $\alpha = \Delta_{med} exp(1 + H_{med}) - exp((1 + \beta) + H_{med})$.

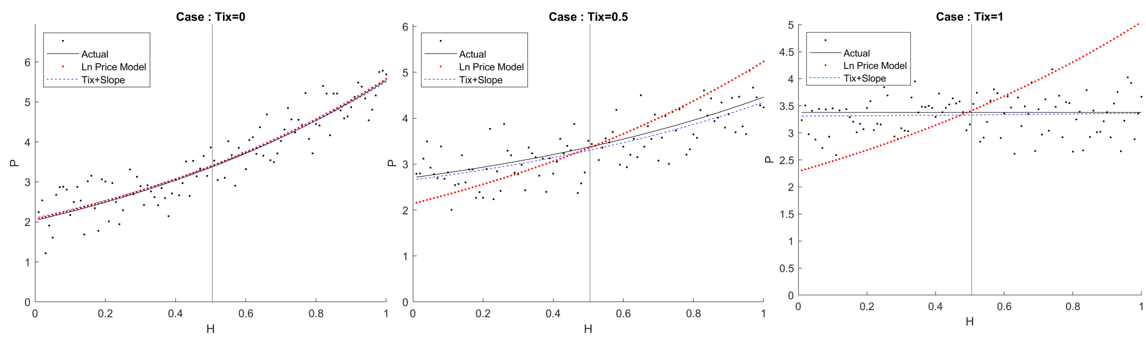
incorrectly imposes an upward sloping premium in the size of the home. This is because the semilog model effectively forces slope-only capitalization, meaning it assumes the premium *must* rise with the size of the home at a constant proportional rate. In other words, to fit the average distance between neighborhoods in the middle of the support of h, a tilt is imposed throughout the distribution of h. In the center column, when tickets comprise half the capitalization, we see the same qualitative pattern of "overtilting," less severe simply because tickets are relatively less important.

To emphasize the point, Panel B displays the premium as a proportion of the low-G neighborhood's price. The semilog model assumes the same proportional increase across homes of all values, and hence the semilog model line is flat in all three cases. When tickets are absent, this is accurate. When tickets are important, the proportional increase in price decrease in the home's size, and the semilog model is tilted through the true premium function from the underside.

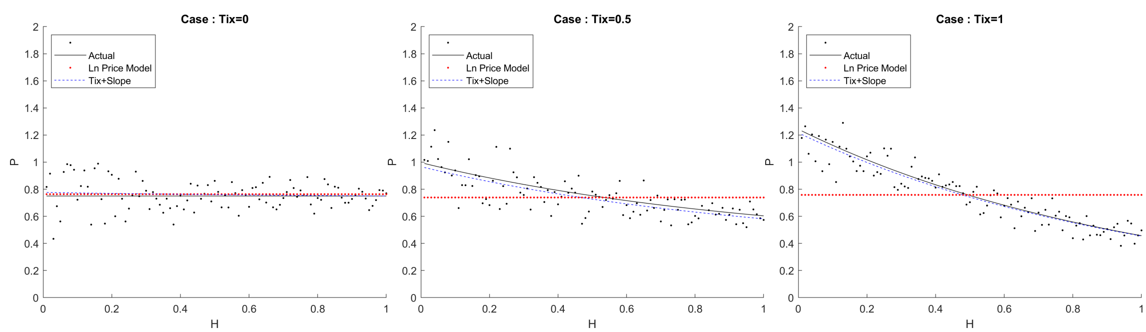
By ignoring tickets, the semilog model produces a premium that rises in the value of the home, as it assumes the same proportional increase in prices across all homes. Ticket capitalization produces a less-steeply rising premium, and one which constitutes a larger proportion of a home's value in small properties. This bias is potentially empirically relevant, with distributional implications.

Figure D1: Capitalization Via Slopes or Tickets

Panel A: Amenity Premium Estimated From Simulated Data



Panel B: Proportional Amenity Premium



NOTES: The figure reports results from a simulation exercise in which amenity capitalization emerges in intercept or slope effects. The leftmost column is slope-only capitalization; the middle column in half intercept/half slope, and the rightmost is intercept-only. The figure plots one representative draw from the simulations.

E Monte Carlo Analysis of the *tixslopes* Estimator

In this section, we evaluate the *tixslopes* estimator through Monte Carlo analysis.

E.1 Data Generating Process

The simulated data comes from a model drawn as

$$p_{inb} = c_0 + \alpha G_n + \delta_a + (\beta(G_n) + \delta_b)H(\gamma, X_i) + \epsilon_i$$

with additive errors, or

$$p_{inb} = [c_0 + \alpha G_n + \delta_a + (\beta(G_n) + \delta_b)H(\gamma, X_i)]\, \epsilon_i$$

for proportional errors. For example, the exp-exp model with two housing attributes and additive errors is

$$p_{inb} = c_0 + \alpha G_n + \delta_a + \exp(\delta_b \beta G_n + \gamma_1 H_{i1} + \gamma_2 H_{2i}) + \epsilon_i$$

And similarly, fully linear and linear-exp combination models are also drawn as possible data generating processes (DGP). This gives four DGPs for additive errors and four for proportional errors. Thus, there are a total of eight possible DGPs with eight possible estimation models, for a total of 64 possible DGP/estimator combinations.

We set $c_0, \alpha, \beta, \gamma_1, \gamma_2$. The ϵ_i are drawn from a standard normal distribution. The amenity values are drawn from a uniform distribution, $G \sim U(0, 2)$. The area fixed effects, δ_a, δ_b are drawn as correlated random numbers. First, δ_a is drawn from $U(0, 0.1c_0)$. Then δ_b is drawn as a mixture, $\delta_b = 0.1\delta_a + \tilde{\delta}_b$, where $\tilde{\delta}_b \sim U(-0.05, 0.05)$.

E.2 Monte Carlo Results

We drew 100 Monte Carlo simulations each with $J = 100$ neighborhoods, $N = 100$ properties in each neighborhood, and $D_n = 2$ spatial groups (meaning one coefficient for a ticket and one for a slope). We report the results from two DGPs, one with the exp-exp model with additive errors, and another with linear-linear model with proportional errors. (We also completed Monte Carlo analyses with for all eight DGPs, and for larger samples and spatial delineations, with results available upon request.)

The parameters we use are:

Parameter	Value	Coefficient of
γ_1	1	H_1
γ_2	0.5	H_2
α	0.3	G, ticket
β	0.15	G, slope
c_0	5.0	Constant

Table E1 reports the mean output from the *tixslopes* estimator function—parameters and WTP and marginal WTP estimates—for each of the eight possible combinations of estimation options. It compares to the true DGP of exponential capitalization and housing services and additives errors (so, model 1 uses the actual DGP). The last model we use, for comparison purposes, is the semilog.

It is clear form the table that when the estimator model matches the functional form of the true DGP, unsurprisingly, the estimator can easily recover the parameter estimates. When the assumed functional form is wrong, the parameters need to be reinterpreted. For example, if the DGP uses $exp(\beta G)$ and the estimator uses βG, the model is trying to best fit $\hat{\beta} = exp(\beta)$ on a transformed regressor.

However, the panel showing the WTP and marginal WTP estimates shows that even a mis-specified functional form can deliver reasonably well approximated expected values and derivatives—as long as the function permits ticket capitalization. The performance of the semilog model is noticeably worse. In particular, we see the effects of bias across the housing services distribution that are illustrated in section D. While the median is well approximated, the semilog model misses too low for small properties and too high for large properties, with the derivative of the capitalization function with respect to G being too high for the former and too low for the latter. This is the consequence of the ticketless model forcing a too-steep gradient through the pricing surface.

Table E2 uses the linear-linear DGP with proportional errors. The conclusions are very similar. The *tixslopes* estimator hits the parameters when the functional form is right and the WTP and MWTP estimates even when it is not. The semilog model again forces a too-steep line of prices over housing services.

Table E1: Monte Carlo Simulations For *tixslopes* Estimator:
When DGP Is Exponential-Exponential Functional Form

		Tickets and Slopes								Semilog
Options:		1	2	3	4	5	6	7	8	9
linhform		0	0	0	0	1	1	1	1	0
linslopeform		0	0	1	1	0	0	1	1	0
prope		0	1	0	1	0	1	0	1	0
actual DGP?		yes								
Parameter	Value									
$\gamma_1 =$	1	1.001	1.002	1.003	1.004	2.243	2.140	2.251	2.148	0.295
$\gamma_2 =$	0.5	0.500	0.501	0.501	0.502	1.117	1.067	1.121	1.071	0.147
$\alpha =$	0.3	0.304	0.305	0.304	0.305	0.391	0.409	0.392	0.410	0.000
$\beta =$	0.15	0.149	0.149	0.153	0.152	0.150	0.147	0.153	0.149	0.084
$c_0 =$	5	4.994	4.973	4.998	4.978	5.495	5.536	5.494	5.535	0.034
(M)WTP	Value									
$E(p)_{25} =$	6.592	6.590	6.571	6.595	6.576	6.451	6.483	6.453	6.485	6.486
$\Delta E(p)_{25} =$	0.099	0.099	0.100	0.100	0.100	0.095	0.098	0.096	0.098	0.109
$(\partial E(p)/\partial G)_{25} =$	0.494	0.496	0.498	0.501	0.501	0.476	0.488	0.479	0.490	0.545
$(dE(p)/dG)_{25} =$	0.494	0.496	0.498	0.501	0.501	0.476	0.488	0.479	0.490	0.545
$E(p)_{50} =$	7.430	7.429	7.412	7.436	7.419	7.577	7.558	7.583	7.564	7.513
$\Delta E(p)_{50} =$	0.124	0.124	0.125	0.126	0.126	0.129	0.129	0.130	0.130	0.126
$(\partial E(p)/\partial G)_{50} =$	0.620	0.621	0.623	0.629	0.629	0.645	0.646	0.651	0.650	0.631
$(dE(p)/dG)_{50} =$	0.620	0.621	0.623	0.629	0.629	0.645	0.646	0.651	0.650	0.631
$E(p)_{75} =$	8.812	8.813	8.799	8.825	8.812	8.703	8.633	8.713	8.642	8.704
$\Delta E(p)_{75} =$	0.165	0.166	0.166	0.168	0.168	0.163	0.161	0.165	0.162	0.146
$(\partial E(p)/\partial G)_{75} =$	0.827	0.828	0.829	0.840	0.839	0.814	0.804	0.823	0.810	0.731
$(dE(p)/dG)_{75} =$	0.827	0.828	0.829	0.840	0.839	0.814	0.804	0.823	0.810	0.731

NOTES: .

Table E2: Monte Carlo Simulations For *tixslopes* Estimator:
When DGP Is Linear-Linear Functional Form

		Tickets and Slopes								Semilog
Options:		1	2	3	4	5	6	7	8	9
linhform		0	0	0	0	1	1	1	1	0
linslopeform		0	0	1	1	0	0	1	1	0
prope		0	1	0	1	0	1	0	1	0
actual DGP?									yes	
Parameter	Value									
$\gamma_1 =$	0.83	0.495	0.503	0.496	0.503	0.829	0.825	0.831	0.827	0.139
$\gamma_2 =$	0.65	0.397	0.398	0.397	0.398	0.647	0.644	0.649	0.646	0.109
$\alpha =$	0.3	0.172	0.167	0.158	0.154	0.300	0.298	0.299	0.297	0.000
$\beta =$	0.15	0.143	0.145	0.158	0.158	0.145	0.146	0.151	0.151	0.067
$c_0 =$	5	4.253	4.219	4.271	4.236	5.000	4.975	5.001	4.976	0.034
(M)WTP	Value									
$E(p)_{25} =$	5.510	5.563	5.526	5.568	5.531	5.508	5.481	5.509	5.481	5.487
$\Delta E(p)_{25} =$	0.066	0.067	0.066	0.067	0.067	0.066	0.066	0.066	0.066	0.073
$(\partial E(p)/\partial G)_{25} =$	0.331	0.335	0.332	0.336	0.333	0.330	0.329	0.330	0.328	0.365
$(dE(p)/dG)_{25} =$	0.331	0.335	0.332	0.336	0.333	0.330	0.329	0.330	0.328	0.365
$E(p)_{50} =$	6.045	5.997	5.964	6.002	5.969	6.042	6.012	6.045	6.014	5.998
$\Delta E(p)_{50} =$	0.082	0.079	0.079	0.081	0.080	0.082	0.081	0.082	0.082	0.080
$(\partial E(p)/\partial G)_{50} =$	0.411	0.397	0.395	0.404	0.401	0.408	0.406	0.410	0.408	0.399
$(dE(p)/dG)_{50} =$	0.411	0.397	0.395	0.404	0.401	0.408	0.406	0.410	0.408	0.399
$E(p)_{75} =$	6.581	6.595	6.570	6.601	6.576	6.577	6.543	6.581	6.548	6.557
$\Delta E(p)_{75} =$	0.098	0.097	0.097	0.099	0.099	0.097	0.097	0.098	0.098	0.087
$(\partial E(p)/\partial G)_{75} =$	0.491	0.483	0.483	0.497	0.496	0.485	0.483	0.491	0.488	0.436
$(dE(p)/dG)_{75} =$	0.491	0.483	0.483	0.497	0.496	0.485	0.483	0.491	0.488	0.436

NOTES: .

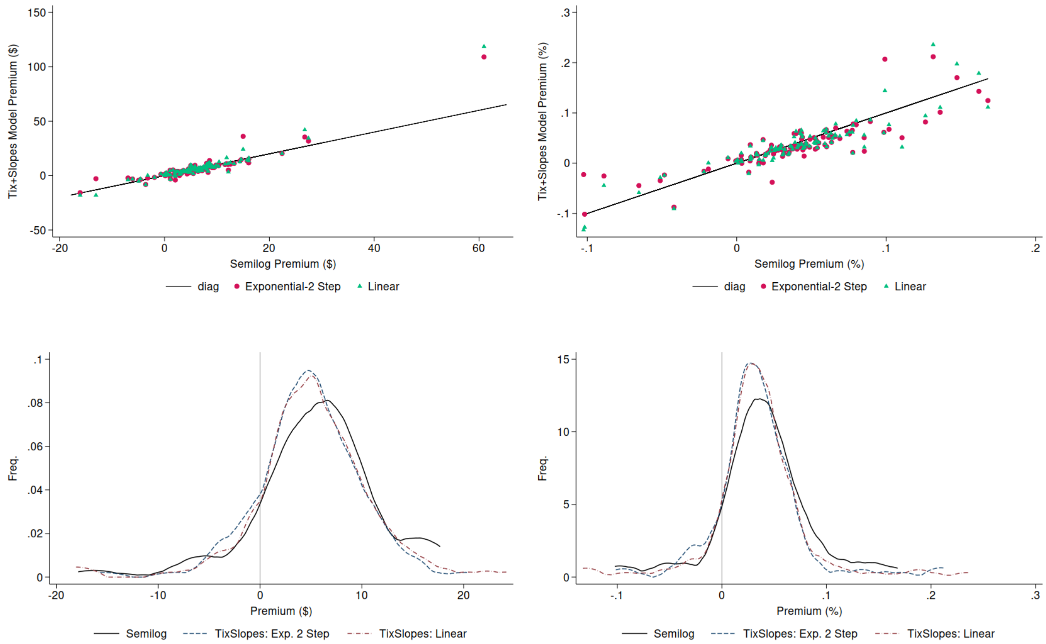
F Summaries of Hedonic Estimates

F.1 Comparing Semilog and Ticket Models Across Markets

Section 7.1 presented several approaches for incorporating tickets into hedonic estimators. Figure F1 shows results from the semilog model of Section 7.2 plotted against three alternative models: the linear model, the two stage model, and the two matching models. The absolute size of the premium can vary across markets for various social and economic reasons outside of our research question—the within-market variance in school quality, the demographics of the market, the outside option to public schools, and likely many other reasons. However, the figure shows that if one city has a high premium in the semilog model, it tends to also have a high premium in the tickets-and-slopes models as well.

Table F1 provides each city's WTP estimates of school quality from our boundary regression discontinuity models for three points in the housing size distribution (25th, 50th, and 75th percentiles). The distribution of estimates is summarized in the main text in Table 5.

Figure F1: Comparison of Premium Estimates Between Hedonic Models: Semilog Versus Tickets and Slopes



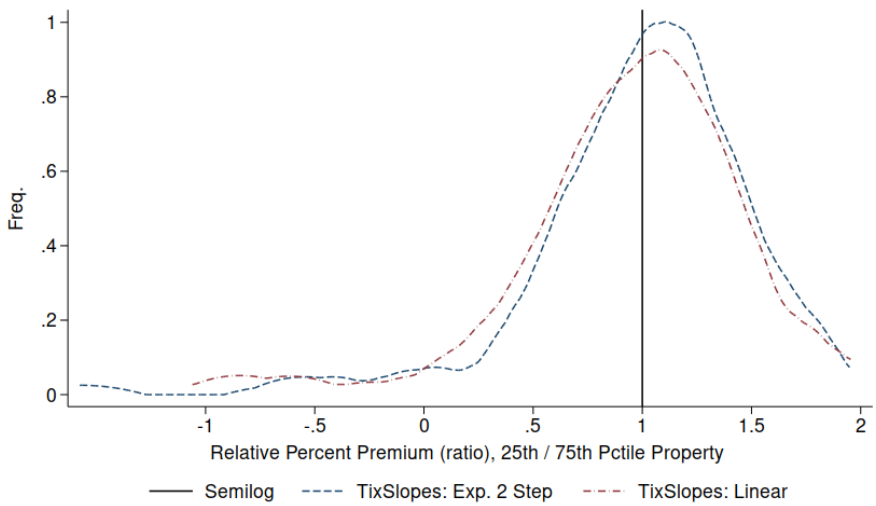
NOTES: The figure plots the ticket-accommodating models, as described in Section 7.1, against the semilog model in their estimates of willingness to pay for a one standard deviation increase in school performance for properties of median size. Each dot corresponds to a unique market (metro area) for the model denoted in the legend. The lefthand figure plots the school test score premium in 1,000s of dollars, and the righthand figure plots the the premia in percentage increase in price.

F.2 The Proportional Price Premium

The semilog model imposes a uniform proportional price premium. We show here that this assumption is violated in many markets in the school quality application.

Figure F2 shows the distribution of the ratio in the percentage price premium between 75th and 25th percentile sized properties. The semilog model is a vertical line at 1 — properties of all sizes have the same proportional capitalization. The ticket-and-slopes models instead show a disperse distribution of proportional price premia. This empirical regularity is ruled out by the semilog model.

Figure F2: Difference in Percentage Premia Estimates for Large and Small Properties



NOTES: The figure portrays the distribution across cities of the ratio in estimated willingness-to-pay, as a fraction of the home price in an average-amenity neighborhood, between a 75th percentile-sized property and a 25th percentile-sized property for the models described in Section 7.1.

Table F1: Willingness to Pay Point Estimates ($1,000), by Model and Property Size Percentile

City, Model	Semilog			Linear			NL 2 Step		
Property Size:	25th	50th	75th	25th	50th	75th	25th	50th	75th
Akron (OH)	3.28	3.58	4.08	3.11	3.41	3.98	3.19	3.68	4.62
Albuquerque (NM)	6.26	6.58	7.07	6.87	7.16	7.74	5.99	6.38	7.17
Asheville (NC)	12.43	14.99	19.76	16.33	24.19	42.17	25.38	36.08	60.54
Atlanta (GA)	4.16	5.00	6.51	9.94	9.83	9.54	9.07	9.21	9.55
Augusta (GA)	6.44	7.48	9.38	7.79	8.33	9.50	7.09	7.39	8.03
Austin (TX)	7.33	7.51	7.77	6.40	6.88	7.97	5.42	6.77	9.82
Bakersfield (CA)	3.96	4.55	5.50	3.80	4.14	4.78	3.33	3.69	4.36
Baltimore (MD)	7.16	7.97	9.26	7.24	7.08	6.76	6.59	6.68	6.85
Baton Rouge (LA)	-15.92	-16.11	-16.42	-20.52	-18.07	-11.61	-16.39	-15.71	-13.93
Birmingham (AL)	3.82	4.29	5.16	3.59	3.50	3.28	1.71	1.57	1.24
Boise City (ID)	2.79	3.20	3.95	3.64	3.21	2.15	4.31	3.55	1.68
Boulder (CO)	12.80	14.62	17.58	14.88	14.93	15.06	14.19	14.64	15.73
Bradenton (FL)	1.37	1.62	2.02	3.82	5.05	7.29	5.08	5.23	5.50
Charleston (SC)	0.93	1.12	1.47	0.57	-3.51	-12.45	-1.93	-3.03	-5.43
Charlotte (NC)	7.54	8.32	9.71	10.81	10.85	10.97	10.88	10.68	10.12
Chicago (Cook) (IL)	2.61	2.86	3.32	0.48	1.19	2.99	0.02	0.12	0.37
Chicagoland (IL)	8.85	10.41	13.46	10.47	12.65	18.45	10.40	10.31	10.05
Chico (CA)	6.76	7.20	7.85	2.26	4.40	8.52	3.02	4.63	7.73
Cincinnati (OH)	10.77	11.86	13.57	13.66	16.46	22.02	9.72	10.99	13.52
Colorado Springs (CO)	3.59	4.16	4.90	4.54	4.49	4.42	3.19	4.03	5.39
Columbia (SC)	7.10	7.09	7.07	5.12	4.86	4.20	3.57	4.82	7.91

Continued on next page

Table F1: Willingness to Pay Point Estimates ($1,000), by Model and Property Size Percentile

City, Model	Semilog			Linear			NL 2 Step		
Property Size:	25th	50th	75th	25th	50th	75th	25th	50th	75th
Columbus (OH)	2.92	3.24	3.73	4.65	3.22	0.60	2.19	2.21	2.25
Corpus Christi (TX)	7.63	8.07	8.72	4.02	5.92	9.67	4.03	5.31	7.84
Corvallis (OR)	7.62	8.58	10.18	16.36	11.89	2.12	17.19	13.81	6.41
Dallas (TX)	5.73	6.17	6.92	5.12	5.59	6.80	4.61	5.04	6.13
Deltona (FL)	1.69	2.06	2.64	-0.95	0.56	3.21	-7.02	-4.05	1.20
Denver (CO)	7.70	9.04	11.10	7.90	9.09	11.50	7.93	8.53	9.74
Des Moines (IA)	0.07	0.08	0.09	0.17	0.02	-0.30	0.44	0.24	-0.18
Detroit (MI)	0.15	0.15	0.15	0.20	0.19	0.15	0.09	-0.02	-0.22
Dover (DE)	4.03	4.63	5.42	2.62	2.93	3.44	2.49	2.42	2.30
Duluth (MN)	15.34	16.05	17.17	12.21	13.59	16.21	10.92	11.70	13.18
Durham (NC)	-0.64	-0.69	-0.78	2.49	1.48	-0.88	1.73	1.19	-0.06
El Paso (TX)	2.72	3.09	3.72	3.38	3.49	3.73	3.03	3.18	3.48
Eugene (OR)	11.89	12.10	12.38	11.10	10.82	10.31	10.51	10.27	9.83
Fayetteville (NC)	5.54	6.43	7.93	5.16	6.59	9.29	5.60	5.86	6.34
Fort Wayne (IN)	1.02	1.13	1.31	0.24	0.53	1.08	0.16	0.34	0.67
Fresno (CA)	5.50	5.81	6.29	9.24	8.60	7.29	10.33	9.43	7.59
Gainesville (FL)	-5.73	-6.11	-6.67	-3.28	-3.23	-3.12	-3.19	-3.13	-3.02
Grand Junction (CO)	0.45	0.51	0.60	0.86	1.10	1.52	1.57	1.29	0.79
Greensboro (NC)	5.74	6.39	7.57	4.32	3.87	2.70	4.50	3.87	2.22
Greenville (SC)	2.89	3.43	4.36	2.79	3.39	4.71	2.92	3.46	4.65
Hartford (CT)	13.45	14.38	16.23	11.75	12.62	15.10	12.76	13.43	15.38

Continued on next page

Table F1: Willingness to Pay Point Estimates ($1,000), by Model and Property Size Percentile

City, Model	Semilog			Linear			NL 2 Step		
Property Size:	25th	50th	75th	25th	50th	75th	25th	50th	75th
Houston (TX)	3.05	3.59	4.42	4.09	4.92	6.61	4.72	4.71	4.69
Huntsville (AL)	0.27	0.31	0.38	1.66	2.80	5.70	1.59	2.16	3.61
Jacksonville (FL)	7.55	8.31	9.57	4.71	4.06	2.71	2.54	2.99	3.92
Kansas City (MO)	2.69	3.05	3.80	3.63	3.64	3.65	3.12	3.31	3.83
Knoxville (TN)	3.79	4.55	6.01	4.97	6.10	8.80	5.50	6.04	7.36
Lakeland (FL)	0.61	0.73	0.91	1.16	0.77	0.14	1.29	0.91	0.31
Las Cruces (NM)	7.85	8.82	10.36	10.57	9.27	6.74	10.50	9.40	7.28
Las Vegas (NV)	0.90	1.04	1.29	4.36	4.54	4.90	5.19	4.88	4.23
Lexington (KY)	13.21	15.76	20.39	14.16	14.35	14.78	13.31	13.61	14.27
Lincoln (NE)	3.85	4.36	5.23	2.94	3.40	4.41	3.10	3.45	4.22
Little Rock (AR)	7.26	8.30	10.11	8.91	8.92	8.94	8.21	8.47	9.03
Los Angeles (LAC) (CA)	4.13	4.55	5.15	4.73	5.85	7.87	5.23	5.70	6.57
Los Angeles (OC) (CA)	14.20	16.09	19.83	16.61	16.20	15.06	15.77	15.31	14.05
Madison (WI)	7.53	8.40	9.59	11.64	11.49	11.21	7.88	9.39	12.01
McAllen (TX)	-3.13	-3.60	-4.40	-7.46	-8.37	-10.34	-7.60	-8.14	-9.28
Medford (OR)	3.23	3.64	4.29	3.05	4.26	6.65	4.04	4.56	5.58
Memphis (TN)	5.64	6.49	8.29	4.78	5.18	6.25	4.25	4.59	5.49
Miami (FL)	11.51	12.57	14.31	10.91	11.91	14.07	9.79	10.47	11.94
Milwaukee (WI)	4.89	5.49	6.34	4.57	5.67	7.70	4.77	6.82	10.56
Minneapolis (MN)	6.63	7.32	8.47	7.19	7.40	7.87	5.93	6.16	6.68
Mobile (AL)	-4.01	-4.61	-5.56	-4.75	-3.07	0.10	-4.63	-3.67	-1.86

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Table F1: Willingness to Pay Point Estimates ($1,000), by Model and Property Size Percentile

City, Model	Semilog			Linear			NL 2 Step		
Property Size:	25th	50th	75th	25th	50th	75th	25th	50th	75th
Myrtle Beach (SC)	-10.89	-13.08	-16.26	-12.80	-18.05	-26.56	1.31	-2.86	-9.62
Naples (FL)	22.95	26.75	33.74	41.18	42.02	43.84	34.56	35.43	37.32
Nashville (TN)	7.41	7.87	8.63	8.08	7.54	6.24	7.25	7.04	6.53
New Haven (CT)	9.24	9.84	11.05	7.22	9.59	15.68	7.44	9.76	15.73
New York City (NY)	53.64	60.96	74.69	118.65	118.60	118.46	109.10	109.04	108.87
New York City (NJ)	2.01	2.02	2.02	3.18	3.18	3.19	1.96	2.85	4.56
Ocala (FL)	-5.99	-6.97	-8.35	-3.50	-3.83	-4.37	-1.38	-2.19	-3.51
Ogden (UT)	7.66	8.37	9.48	8.32	8.08	7.63	8.01	7.77	7.31
Oklahoma City (OK)	4.73	5.45	6.83	4.59	6.35	10.31	4.47	5.53	7.91
Omaha (NE)	0.70	0.76	0.85	0.21	0.71	1.70	0.03	0.44	1.27
Orlando (FL)	4.24	4.68	5.38	3.58	3.78	4.21	3.19	3.43	3.91
Ventura (CA)	22.82	27.46	34.20	38.03	34.39	27.31	35.18	31.76	25.11
Melbourne (FL)	-1.65	-1.92	-2.36	-2.63	-1.75	-0.09	-2.19	-1.62	-0.56
Panama City (FL)	11.24	12.18	13.49	1.99	3.26	5.51	5.85	5.13	3.88
Pensacola (FL)	3.56	3.95	4.48	3.32	3.74	4.48	3.41	3.62	3.99
Philadelphia (PA)	7.40	7.83	8.66	6.08	7.21	10.29	6.05	6.77	8.70
Phoenix (AZ)	4.46	5.14	6.36	9.86	9.21	7.82	8.65	8.49	8.15
Pittsburgh (PA)	11.94	13.28	15.51	10.37	10.91	12.03	11.24	11.19	11.10
Portland (OR)	6.57	6.98	7.66	6.39	6.46	6.63	5.54	5.96	6.88
Provo-Orem (UT)	2.30	2.60	3.06	3.86	3.66	3.18	4.25	3.86	2.95
Racine (WI)	-4.70	-4.92	-5.26	-4.76	-5.12	-5.80	-4.22	-4.17	-4.06

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Table F1: Willingness to Pay Point Estimates ($1,000), by Model and Property Size Percentile

City, Model	Semilog			Linear			NL 2 Step		
Property Size:	25th	50th	75th	25th	50th	75th	25th	50th	75th
Raleigh (NC)	-0.09	-0.10	-0.13	2.08	0.66	-2.64	1.76	0.78	-1.50
Reno (NV)	10.84	11.55	12.74	11.54	10.65	8.57	10.79	10.17	8.71
Richmond (VA)	5.86	6.44	7.32	5.39	5.48	5.68	4.20	4.98	6.70
Riverside (CA)	1.98	2.30	2.93	3.43	3.84	4.88	3.50	3.77	4.47
Roanoke (VA)	1.78	1.99	2.25	2.42	3.16	4.31	3.25	3.43	3.72
Sacramento (CA)	4.39	4.99	6.12	7.00	6.91	6.69	5.46	5.95	7.06
St. Louis (MO)	2.79	3.39	4.57	1.71	3.22	7.22	2.76	3.25	4.54
Salem (OR)	4.89	5.02	5.24	3.56	3.17	2.28	3.30	3.02	2.39
Salt Lake City (UT)	5.14	5.77	6.62	8.06	7.39	6.18	7.13	6.92	6.56
San Antonio (TX)	0.07	0.08	0.10	0.61	0.93	1.62	0.61	0.85	1.38
San Diego (CA)	7.32	8.18	9.43	8.30	8.64	9.24	8.32	8.32	8.33
San Francisco (CA)	7.33	8.03	9.19	9.28	10.43	12.93	9.05	11.31	16.23
San Jose (CA)	21.66	22.42	23.36	18.15	20.38	23.99	16.78	20.36	26.13
Savannah (GA)	5.98	6.55	7.70	3.96	4.42	5.62	3.77	4.29	5.63
Seattle (WA)	6.43	6.93	7.63	8.12	7.30	5.66	7.29	6.76	5.72
Stockton (CA)	5.41	6.05	7.03	3.79	4.92	7.10	3.97	4.66	5.98
Tampa-St. Pete. (FL)	8.83	9.54	10.61	6.31	7.59	10.05	7.20	7.65	8.53
Tucson (AZ)	1.87	2.06	2.34	-0.47	-0.48	-0.51	0.34	-0.03	-0.74
Tulsa (OK)	1.75	1.95	2.31	0.56	0.90	1.65	1.76	1.60	1.24
Norfolk (VA)	8.25	9.07	10.60	6.96	7.61	9.18	7.32	7.36	7.47
Visalia (CA)	8.77	9.41	10.45	8.52	7.88	6.55	7.69	7.41	6.83

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Table F1: Willingness to Pay Point Estimates ($1,000), by Model and Property Size Percentile

City, Model	Semilog			Linear			NL 2 Step		
Property Size:	25th	50th	75th	25th	50th	75th	25th	50th	75th
Washington (DC)	4.85	5.36	6.28	5.98	6.04	6.19	5.98	5.88	5.63
Wichita (KS)	2.60	3.09	3.82	1.47	1.71	2.17	1.90	1.75	1.46
Wilmington (NC)	-2.79	-3.22	-3.95	0.88	0.11	-1.55	-4.15	-2.26	1.84
Winston (NC)	4.17	4.99	6.43	5.35	6.15	7.89	4.88	5.40	6.54
Worcester (MA)	9.68	10.30	11.74	7.43	8.58	12.94	8.21	9.05	12.22
Youngstown (OH)	4.76	5.49	6.47	1.71	1.73	1.78	2.21	1.89	1.37

Models are estimated separately on each market. Source: Authors' calculations using housing and school attendance area data as described in Section 3.

G Documentation for the *tixslopes* Function: Tickets and Slopes Through Nonlinear Least Squares

The function *'tixslopes'* estimates the hedonic models of Section 6 through nonlinear least squares (NLS).

G.1 Estimation Objective

The objective function is

$$Q = min\sum_{i}^{N}(R_iW_iR_i)$$

where R_i is the residual for an observation i, and W_i is the observation's weight. The residual for an observation is the difference between the realized price and model-predicted price at the parameter vector θ.

$$R_i = p_i - M(\theta, G, H)$$

When assuming a proportional error structure, the residual is

$$R_i = \ln(p_i) - \ln(M(\theta, G, H))$$

The observation weights, W_i, are optional.

G.2 Features of the Estimator

The expected data structure consists of individual property pricing observations, individual property attributes (or a pre-specified housing services index), and amenities defined by spatial units (e.g., neighborhood schools).

It takes as **required arguments:**

1. Price observations (e.g., sales or rents), p_i. These are scalars and must be strictly greater than zero.
2. Housing attributes (e.g., living area, land/lot area, bedrooms), H. These can be continuous or categorical, but the user must convert any categorical attributes to vectors of dummy variables beforehand.

3. A discrete spatial definition (mutually exclusive spatial units such as neighborhoods). This is a vector of codes; i.e., categorical variables such as definitions of neighborhoods $1, ..., J$.

4. Local amenities defined at the spatial unit level or finer, G. These are treated as continuous variables. The user must input a normalization value; for example, the average value of G. This is necessary because the scale of slope-by-housing services interaction is not identified.

5. A categorical variable for wider spatial units, such as area fixed effects in both tickets and slopes. If there are none, this degenerates into a constant.

It takes as **optional arguments:**

1. An indicator for using the linear housing services model (default is the exponential form).

2. An indicator for using the linear slope capitalization model (default is the exponential form).

3. An indicator specifying the error structure (default is additive errors).

4. A vector of observation weights (default is unitary weight).

The outputs are parameter estimates and robust standard errors. The estimate of the variance-covariance matrix is computed as

$$A\hat{var}(\theta) = \sum_{i}^{N} (dM_i \, dM')^{-1} (dM(R_i)^2 dM')(dM \, dM')^{-1}$$

where $dM = [\frac{dM}{d\theta_1} \cdots \frac{dM}{d\theta_k}]'$ is the gradient of the objective function with respect to each parameter $(1, ..., K)$ for the ith observation, i.e., the score vector. This is a standard robust standard error formula for M-estimators, including nonlinear least squares.

The routine first generates starting values before proceeding to the full nonlinear distance minimization step. The function uses the most commonly available minimization option in the statistical package (e.g., *fminsearch* in Matlab and *optim* in R).

G.3 Hedonic Willingness to Pay

An optional post-estimation function uses the parameter estimates and associated variance-covariance matrix to generate estimates of hedonic willingness to pay (WTP) and marginal WTP (MWTP) at specified values of housing attributes and amenity values. The WTP is the projected property price at the bundle of an amenity value g_i and housing attributes, H_i,

$$\hat{p} = E(p|G = g_i, H = H_i)$$

.

The function also provides the change in price as the property moves from one level of G to another,

$$\Delta\hat{p} = E(p|G = g_i, H = H_i) - E(p|G = g_j, H = H_i)$$

.

The MWTP is the change in the WTP with respect to the amenity at these specified values of g and H,

$$\frac{dE(p)}{dG}|_{G_i,H_i}$$

.

The function outputs the analytic derivative based on the chosen functional form as well as the approximate derivative at the midpoint of two user-supplied values of g_i, holding fixed H_i. Standard errors of these estimates are computed using the delta method.

G.4 Function Syntax

We provide code written for R and Matlab that implements the basic tickets-and-slopes estimator and the two-step boundary fixed effects estimator.

The function syntax for the tickets-and-slopes estimator is as follows.

tixslopes **: Parameter Estimation**

The function is

[B_se,AVAR]=f_tixslopes($P, H, G, G_n, D_n, \bar{G}$).

- Outputs.
  - B_se : Parameter estimates with robust standard errors
  - $AVAR$: The variance-covariance matrix of the parameter vector. This is an optional output, but it is a necessary input into the WTP function.
- Required inputs
  - P: observed prices of properties
  - H: Matrix of housing attributes. Note that the function assumes the user has converted beforehand any categorical attributes to vectors of dummy variables.
  - G: Matrix of amenities for which hedonic prices are evaluated.
  - G_n : vector of categorical identification variables for the neighborhood units at which G is defined.
  - D_n: vector of categorical identification variables for wider-area fixed effects. If there are none, enter a vector of ones.
  - $\bar{G}$: The normalizing value of G
- Options
  - *linslopeform*: Set ('linslopeform',1) if desiring to run the linear slope capitalization model. The default is the exponential version.
  - *linhform*: Set ('linhform',1) if desiring to run the linear housing services model. The default is the exponential version.
  - *prope*: Set ('prope',1) if desiring to impose a proportional error structure on the distance minimization routine. The default is additive errors.
  - *Weights*: Set ('Weights',W), where W is a vector of observation weights, in order to run weighted least squares. The default is unitary weights.

tixslopes: WTP Estimation

A post-estimation command provides a way to estimate WTP and MWTP at user-supplied values of G and H

The function is

[p_hat,delp_hat, dpdg, delpdg]=f_tixslopes_wtp_ath($B\_se, AVAR, G_1, H_i, G_2, \bar{G}$).

- Outputs.
  - p_hat, $\hat{p}_1$: The predicted price at G_1,H_i.
  - delp_hat, $\Delta\hat{p}$: The change in predicted price between G_1 and G_2 at H_i.
  - dpdg, ${}^{\partial\hat{p}_m}/_{\partial G}|_{G_m}$: The analytic derivative of the predicted price at G_m,H_i.
  - delpdg, ${}^{\Delta\hat{p}_m}/_{\Delta G}|_{G_m}$: The approximated derivative of the predicted price at G_m,H_i, calculated as the difference in prices divided by the differences in G between G_1, G_2.

  Each of these quantities is reported with a robust standard error calculated using the delta method.

- Required inputs
  - B_se: The parameter estimates from *f_tixslopes*.
  - $AVAR$: The variance-covariance matrix from from *f_tixslopes*.
  - G_1: A value of amenity; a scalar.
  - H_i: A vector of housing attributes.
  - G_2: A second value of an amenity.
  - $\bar{G}$: Normalizing value for amenities.
  - * G_m: Note: G_m is calculated as the midpoint between G_1 and G_2 and does not need to be supplied separately

- Options
  - *linslopeform*: Set ('linslopeform',1) if using the linear slope capitalization model. The default is the exponential version.
  - *linhform*: Set ('linhform',1) if using the linear housing services model. The default is the exponential version.
  - * Note: The user is responsible for enforcing consistency of functional form between the estimation and post-estimation WTP.

tixslopes_bndy: **Parameter Estimation in Boundary Models via Two-Step Estimator**

This function estimates (14), obtaining the ticket and slope parameters for a single focal amenity in an environment with boundary fixed effects. Note that this only applies to the exp-exp model.

The function is

[B_se,AVAR]=f_tixslopes_bndy($P, H, G, D_n, Gp, Wp, \bar{G}$).

- Outputs.
  - B_se : Parameter estimates with robust standard errors
  - $AVAR$: The variance-covariance matrix of the parameter vector, accounting for the two step estimation variances as in Newey (1984).
- Required inputs
  - P: observed prices of properties
  - H: Housing services as a single index. Note that the model does not estimate service index parameters.
  - G: Focal amenity value for property i.
  - D_n: Categorical variables identifying the boundary group.
  - G_p. The pair of amenity values for the boundary group i belongs to. This requires the user to assign a "side 1" and "side 2," arbitrarily but consistently across each property in the boundary group.
  - W_p. The weights (e.g., relative number of observations drawing from each side of the boundary) for boundary group i belongs to. This requires the user to assign a "side 1" and "side 2," arbitrarily but consistently across each property in the boundary group, and then calculate weights accordingly. For example, if the sample is exactly balanced (e.g., a matched pair sample), the weights would be 0.5 for each side.
  - $\bar{G}$: The normalizing value of G.
- Options
  - *prope*: Set ('prope',1) if desiring to impose a proportional error structure on the distance minimization routine. The default is additive errors.

– *Weights*: Set ('Weights',W), where W is a vector of observation weights, in order to run weighted least squares. The default is unitary weights.

G.5 An Example Estimation

For the user to ensure they are interacting with the function codes correctly, we include a particular example as a test case. We draw one simulation of the exp-exp model with additive errors,

$$p_{inb} = c_0 + \alpha G_n + \delta_a + \exp(\delta_b \beta G_n + \gamma_1 H_{i1} + \gamma_2 H_{2i}) + \epsilon_i$$

and we provide our estimates when using the function code. Function users should expect to get very similar but perhaps not identical answers, as machines can differ slightly in terms of precision, optimization options, and so on.

G.6 Files Demonstrating the Example

The included files are as follows.

- "example_hedonic_data.csv"

is the simulated data file. It is intended to mimic data in the format a typical user might encounter. Its columns are as delineated in

- "example_hedonic_data_vars.csv"

which are:

1. price , The property price
2. H attribute 1 , A continuous housing attribute.
3. H attribute 2 , A discrete housing attribute.
4. G-index , The value of G_n, the "neighborhood" amenity.
5. G group ID , An ID variable for the "neighborhood" grouping that produces G_n.
6. D group id , An ID variable for the wider spatial grouping that produces δ_a, δ_b.

- "example_hedonic_data_parms.csv"

The parameters used to simulate the data and the results from 8 versions of estimating the model. The rows are

Parameter	True Value	Coefficient of
γ_1	1	H_1
γ_2	0.5	H_2
α	0.3	G, ticket
β	0.15	G, slope
δ_a	≈ 0.727	D_n group ticket
δ_b	≈ 0.064	D_n group slope
c_0	5.0	Constant

• "example_hedonic_data_parms_vars.csv"

Labels on the parameter values, as follows.

1. actual, The values used to simulate the data
2. Hexp-Gexp-add: B , Coefficient from model linhform=0, linslopeform=0, prope=0
3. Hexp-Gexp-add: se , SE from model linhform=0, linslopeform=0, prope=0
4. Hexp-Gexp-prope: B , Coefficient from model linhform=0, linslopeform=0, prope=1
5. Hexp-Gexp-prope: se , SE from model linhform=0, linslopeform=0, prope=1
6. Hexp-Glin-add: B , Coefficient from model linhform=0, linslopeform=1, prope=0
7. Hexp-Glin-add: se , SE from model linhform=0, linslopeform=1, prope=0
8. Hexp-Glin-prope: B , Coefficient from model linhform=0, linslopeform=1, prope=1
9. Hexp-Glin-prope: se , SE from model linhform=0, linslopeform=1, prope=1
10. Hlin-Gexp-add: B , Coefficient from model linhform=1, linslopeform=0, prope=0
11. Hlin-Gexp-add: se , SE from model linhform=1, linslopeform=0, prope=0
12. Hlin-Gexp-prope: B , Coefficient from model linhform=1, linslopeform=0, prope=1
13. Hlin-Gexp-prope: se , SE from model linhform=1, linslopeform=0, prope=1
14. Hlin-Glin-add: B , Coefficient from model linhform=1, linslopeform=1, prope=0

15. Hlin-Glin-add: se , SE from model linhform=1, linslopeform=1, prope=0

16. Hlin-Glin-prope: B , Coefficient from model linhform=1, linslopeform=1, prope=1

17. Hlin-Glin-prope: se , SE from model linhform=1, linslopeform=1, prope=1

- "example_hedonic_data_wtp50.csv", "example_hedonic_data_wtp25.csv", "example_hedonic_data_wtp7

The implied WTP estimates from each of the 8 assumed versions of the estimation. These follow the same order as the parameter estimates above and come from the WTP post-estimation function, which requires specified values for $G = g_j$ and $H = H_{1i}, H_{2i}$. We use the medians of H attributes and the $25^{th}, 50^{th}$, and 75^{th} percentiles of G. The suffix on the file indicates the property percentile.

The rows are

1. Price at the value of the midpoint of G_j, G_k at H
2. The change in price at H between G_j, G_k.
3. The analytic derivative of price with respect to G at H at the midpoint between G_j, G_k.
4. The numerical derivative of price with respect to G at H, using the difference between G_j, G_k.

Notably, the function requires the specification of two values of G to bracket the level of G of interest, so we use $+10, -10$ percentile deviations. These are spelled out in the files:

- "example_hedonic_data_evalpoints.csv" , "example_hedonic_evalpoints_vars.csv"