FEDERAL RESERVE BANK
PHILADELPHIA

Working Papers
RESEARCH DEPARTMENT

Capitalization as a Two-Part Tariff

The Equilibrium Structure of Housing Prices

H. Spencer Banzhaf
North Carolina State University, PERC, and NBER

Kyle Mangum
Federal Reserve Bank of Philadelphia

WP 19-20

PUBLISHED
March 2019

REVISED
October 2025

ISSN: 1962-5361

DOI: https://doi.org/10.21799/frbp.wp.2019.20

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

H. Spencer Banzhaf† Kyle Mangum‡

November 2024

Abstract

This paper investigates whether neighborhood amenities are capitalized into housing prices via a two-part tariff: an extensive margin price for housing of any size or quality and an intensive margin price that raises the price per unit of housing services. A stylized model shows that extensive margin pricing will emerge when there are frictions (such as density regulations) to the allocation of housing across space. Using a data set of housing transactions across markets of the United States, we show that two-part tariff pricing is ubiquitous and especially pronounced in markets with high regulation and older housing stock. Two-part pricing is relevant for hedonic estimation of local amenities: in particular, ignoring it will understate the poorer households' willingness to pay for nonmarketed goods such as public schools.

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

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

---

*We thank David Albouy, Jan Brueckner, Bill Fischel, and Edson Severnini for helpful discussions, as well as numerous conference and seminar participants. We thank Ben Harrell, Bret Hewett, Alexander Gordon, Hal Martin, Cody Reinhardt, Jacob Siegel, Vicky Sparks, and Solomon Tarlin for research assistance. We thank the Lincoln Institute of Land Policy for financial support of this research while each author was on faculty at Georgia State University. Banzhaf is additionally grateful to PERC for a Lone Mountain fellowship to work on this project.

†North Carolina State University, PERC, and NBER. spencer_banzhaf@ncsu.edu

‡Federal Reserve Bank of Philadelphia. kyle.mangum@phil.frb.org.

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, and with households "voting with their feet" to find the jurisdictions with a desirable mix of amenities. But this market analogy raises the question of just what serves as a price of those amenities. Tiebout's simple model assumed that it was non-distortionary head taxes. As with a price in a well-functioning market for private goods, the head tax coordinates the distribution of amenities: Households sort into communities based on their differing demands for amenities, with high-demand households paying a higher tax and receiving more amenities, low-demand types receiving less, and so on. But, households still must purchase housing, so there is a two-part tariff: at the extensive margin, one must purchase a "ticket" to enter the community and receive its benefits (the head tax), and then one must purchase land and housing, with bigger houses costing more at the intensive margin.

Of course, in the real world, jurisdictions typically use property taxes, an *ad valorem* tax. This would seem to imply there is only a single gross-of-tax price of housing, with no two-part tariff as in Tiebout's model. Accordingly, most economists doing empirical analysis of Tiebout models have ignored the role of tickets at the extensive margin. This includes hedonic price regressions, which often use a semilog functional form that restricts amenity values to be a constant percent of housing values (Avenancio-León & Howard, 2022; Banzhaf, 2021; Bishop et al., 2020, e.g.). It also includes structural models of locational choice, which almost invariably assume prices are proportionate in some bundle of housing services (see e.g. Kuminoff, Smith, & Timmins, 2013, for a review). This departure from Tiebout's idealized model gives rise to a potential "jurisdictional choice externality," in which households seeking high amenities can free ride on neighbors by buying the smallest house on the block (Calabrese, Epple, & Romano, 2011).

Hamilton (1975, 1976) extended Tiebout's model to account for just such issues (see also Fischel, 2001, for discussion). He 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 community-level price that mimics Tiebout's head tax. Empirically, Glaeser and Gyourko (2003), Glaeser, Gyourko, and Saks (2005), Gyourko and Krimmel (2021), and Turner, Haughwout, and Van Der Klaauw (2014) have confirmed that building restrictions do increase housing prices, especially at the extensive margin. However, they do not consider how this mechanism affects the capitalization of amenities in prices across communities.

In this paper, we clarify how and when land-use restrictions create tickets and show that they can fundamentally change the way amenities are capitalized into local housing values in ways that have not previously been considered. In short, in the presence of such restrictions, amenities can be capitalized into the tickets as well as into unit prices for land or housing services.

Beginning with a theoretical model, we show that the presence of tickets—and capitalization of amenities into them—depends on land-use restrictions that bind on the number of lots (or housing units) in a neighborhood. Regulations that bind only on other dimensions, such as minimum lot sizes, are not likely to generate such tickets. To our knowledge, this point has not previously been recognized. Nevertheless, in practice, there are myriad frictions—zoning of use, regulatory constraints to new housing, durability of past housing investments, and the like—that do bind on the number of housing units. Hence, one is left to expect that tickets will frequently show up in the housing market.

To test our theory, we compile a data set of over 140 metro areas in the United States, with observed transaction prices and property attributes (such as land and structure sizes), placed into over 20,000 neighborhoods defined by elementary school attendance zones. We derive the pricing functions for these neighborhoods under alternative assumptions about the nature of housing services. Then, in a final step, we use data on local amenities (school achievement scores in addition to environmental and other spatial amenities), to estimate the extent to which neighborhoods are priced by quality according to shifts in levels (tickets) or per unit of services.

We find that, overall, 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 20 percent, 87 percent of which 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 premium for the "nicer" neighborhood is 27 percent, nearly all of which is due to the higher ticket price. This general result is robust to alternative specifications of housing services and alternative measures of land-use restrictions, taken at the metro level or more local level. However, consistent with our theory, we find less effect from minimum lot size restrictions when we parse them out from other land-use restrictions. We also find that markets with an older housing stock, which may be another kind of *de facto* friction on land uses, also capitalize amenities more into tickets.

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 misspecified. Often, these models regress the log of housing values on observable characteristics. This specification imposes the restriction that a change in amenities affects prices multiplicatively, or in percentage terms, which will be incorrect if there is capitalization into tickets. Similar problems plague any structural model of locational choice that ignores community-level extensive margin prices.

Third, our findings have important distributional implications. Common methods that forced 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, regardless of house size. Acknowledging the existence of tickets implies both that the poor are paying more for amenities than standard models imply and that, therefore, by revealed preference, they are willing to do so.

We illustrate these insights with both simulations and with an empirical application to public schools. In our application, we estimate border-discontinuity models (Bayer, Ferreira, & McMillan, 2007; Black, 1999) to recover the implicit price of a unit of school quality (as measured by achievement) separately for all the available metro areas in our data. In one version of estimation, we use a typical semilog model, with logged price as the dependent variable; in others, we use price levels as the dependent variable and allow for ticket and slope capitalization, using nonlinear models that nest the semilog model as a special case. We find a pattern in line with our theory. In the two-part tariff models, we find that the 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 much lower value to school quality for occupants of smaller homes. Thus, we show that ignoring tickets, as the standard semilog hedonic model does, has substantial implications for findings about distributional disparities.

The rest of the paper proceeds as follows. Section 2 presents a model of housing market capitalization to demonstrate how and why two-part tariff pricing will emerge in equilibrium and how it affects capitalization of amenities. Section 3 describes the data in our empirical application, and Section 4 our strategy for recovering the pricing function of neighborhoods. Section 5 presents our results testing for the existence of two-part pricing in U.S. housing markets. Section 6 provides an empirical application to the valuation of public school improvements. Section 7 concludes.

2 Conceptual Framework

In a pair of influential papers, Hamilton (1975, 1976) argued that zoning could replicate the head tax present in Tiebout's (1956) model, thus internalizing the jurisdictional choice externality. Hamilton (1975) offered a model in which the number of jurisdictions was large relative to the population, so minimum lot sizes induce perfect sorting across communities, which are internally homogeneous with respect to lot size and demand for amenities.[1] In contrast, Hamilton (1976) offered a model in which communities had an exogenously set heterogeneous stock of housing, and fiscal transfers created a premium for smaller houses. These papers have provided tremendously important insights and sparked fruitful debates. But, in our view, the literature's long focus on those special cases has underestimated the generality of the insights while also obscuring the specific factors that generate tickets.

In this section, we generalize those models while isolating the key factors that generate tickets. First, to set a baseline for comparison, we consider a hedonic equilibrium with finite land supply but no frictions to housing supply whatsoever. Then, to see the precise effects of land-use controls, we distinguish between two cases: restrictions constraining the total number of lots (or housing units) and restrictions constraining the minimum size of lots. We argue that it is restrictions on the total number of lots that induce two-part pricing with "tickets," whereas minimum lot sizes do not generate tickets except in the special case emphasized by Hamilton, where the two are equivalent.

2.1 Hedonic Equilibrium with No Land-Use Controls

Consider a city with distinct neighborhoods indexed $1...n...N$, as well as an outside option, location 0. The outside option has a perfectly elastic supply of land available at a given price. In the city, neighborhoods are ordered by a scalar-valued composite of exogenous amenities and local public goods, G_n. Each neighborhood in the city has a fixed land area. To focus attention on the (realistic) case where land-use restrictions prevent an optimal configuration of lots, we take as given an initial situation where each neighborhood is carved in an arbitrary number of lots, each of arbitrary size.

On the demand side of the land market, a finite, countable set of heterogeneous households $1...i...I$ have preferences that are monotonic in G, land consumption h, and numeraire consumption k. These preferences can be represented by a strictly increasing differentiable utility function $u_i(k, G, h)$. Households choose the neighborhood n and lot l which maximizes their utility, given a (possibly non-linear) price function over lot size in the neighborhood,

[1] See also Brueckner (1981, 2023) for an extension and rigorous proof of Hamilton's results.

$p_{ln} = p_n(h_{ln})$. (Note that because G_n is uniform within neighborhoods, its effect on prices comes entirely through the neighborhood-specific price function.) The equilibrium price function ensures that each lot is occupied. Given the utility function, the pricing function is continuous and increasing in h within a neighborhood, and at a given h, increasing in G across neighborhoods. This equilibrium represents the standard hedonic model. We assume for exposition that each price function is differentiable in h, but this is not necessary.

Now consider the possibility of assembling or subdividing lots. Developers serve as arbitrageurs who can buy land from existing lots and add land to other lots, or create new ones. Consider first for purposes of comparison the case with no land controls and fully malleable lots. An equilibrium price function must equalize the *marginal value* of land at each lot within a neighborhood, otherwise developers would arbitrage the difference by re-allocating 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 (e.g., dollars per square foot). Otherwise, if the marginal value were higher than the average value, developers could make profits by assembling land so the neighborhood had fewer, larger lots. Alternatively, if the marginal value were lower than the average value, developers would subdivide lots to create more, smaller lots. Thus, without land-use restrictions, the following two equilibrium conditions must hold:

$$\frac{\partial p_n}{\partial h}|h_{ln} \;= \beta_n \text{ for all } l, n \tag{1}$$
$$\frac{\partial p_n}{\partial h}|h_{ln} \;= \frac{p_{ln}}{h_{l,n}} \text{ for all } l, n \tag{2}$$

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

Integrating equation (1) gives

$$p_{ln} = \alpha_n + \beta_n h_{ln} \tag{3}$$

for some constant of integration α_n. Dividing by square footage gives $p_{ln}/h_{ln} = \alpha_n/h_{ln} + \beta_n$. Equation (2) then requires α_n=0 except in the degenerate case where h_{ln} is a constant h_n, precisely the special case considered by Hamilton (1975), Brueckner (1981), and Brueckner (2023).

Consequently, $p_n(h_{ln}) = \beta_n h_{ln}$. That is, because of the no-arbitrage condition at the extensive margin, there are no tickets in the community—for if there were, the average value of land would be higher than the marginal value and developers would re-arrange land into more lots. Instead, there is a single price per square foot in the neighborhood,

β_n. Additionally, the price per square foot across neighborhoods must be strictly increasing in G. Otherwise, as utility is increasing in G, no households would choose to live in the neighborhood with lower G and higher prices.

This model represents the consensus view of hedonic pricing, with amenities capitalized into the per-unit price of land or housing.

2.2 The Effect of Reconfiguration Costs on the Hedonic Equilibrium

We next relax the assumption of full malleability. In reality, there are numerous regulations that effectively limit the number of lots in a neighborhood. One straightforward example is the case of transferable development rights (TDRs), which set a quota on the number of allowable lots and allow these quotas to be traded in the market (McConnell and Walls (2009)). Another specific example is a requirement for low-income housing or other rules that force a particular mix of small and large housing units in the same neighborhood (and prevent arbitrage). More broadly, one can imagine myriad rules preventing the construction of units (e.g., density or height restrictions),[2] or generally inhibiting stock adjustment, locking in buildings or divisions of land now out of equilibrium (historical preservation requirements, difficulty obtaining permits, holdup problems, etc.). Such frictions effectively restrict the number of housing units.

In this case, the higher cost of land in a high-G neighborhood, which emerged in Section 2.1, cannot guarantee that the price clearing the land market results in the number of lots being equal to the constrained number. There may be "too many" small lots. In general, there are now two equilibrium conditions to meet, market clearing in the number of lots as well as in total land, and one price alone cannot guarantee both conditions are met. To the contrary, the additional quantity constraint on lots creates a shadow price on lots *per se*.

To see this, consider some neighborhood $n > 0$ with a binding constraint on the number of lots. Conditional on the number of lots, equilibrium condition (1) still is satisfied, i.e., $\partial p_n/\partial h_{ln} = \beta_n$, otherwise developers could increase their profits by redistributing land from one lot to another (without changing the number of lots). Thus, Condition (3) also is satisfied, so $p_{ln} = \alpha_n + \beta_n h_{ln}$ for some constant of integration α_n. However, equilibrium condition (2), marginal versus average price, is no longer satisfied. Instead,

$$\partial p_n/\partial h_{ln} < p_{ln}/h_{l,n}.$$

[2]Note that here we mean restrictions on units in the neighborhood–e.g., single family zoning only–not necessarily minimum lot size restrictions.

The marginal value of land at the intensive margin is lower than its value at the extensive margin, so developers would like to shrink the lots (in size) to create new ones (in number), but they are restricted from doing so. As a consequence, the average value is shrinking in the 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; see also Glaeser and Gyourko 2018 for a review). The ticket is the shadow value of the constraint on the number of lots.[3]

Crucially, we should expect ticket prices to be increasing in G. To see this, consider an equilibrium in which $G_n = G_{n+1}$ and binding constraints on the number of lots create tickets in both neighborhoods. Now imagine an increase in G_{n+1}. Unless land demand is strongly complementary to G, we would not expect much increase in land demand from current residents in $n+1$. But with higher G and no increase in land prices, we would expect more people to want to enter $n+1$ (and fewer to enter n). This will increase the ticket price in $n+1$ relative to n.[4] Thus, amenities can be capitalized into tickets as well as into housing services.

2.3 The Effect of Minimum Lot Sizes on the Hedonic Equilibrium

Consider finally the case where the city adopts land-use controls in the form of a minimum lot size $\underline{h}$ and where this restriction is binding at least at some lots in at least some neighborhoods, but not necessarily all. The case where it is never binding is obviously equivalent to the fully malleable case. The case where it is binding on *all* households is effectively a constraint on the number of lots, as it is impossible to take land from anywhere and form an additional lot. This degenerate case is thus like the model of the previous sub-section, but with lots of homogeneous size.

In the general case, lot size restrictions may *affect* density in equilibrium, but they are not *binding* on density, in the sense that the equilibrium number of lots is less than the total land area divided by $\underline{h}$. Moreover, developers still can re-arrange land to ensure conditions

[3]Hamilton (1976) provided one explanation for why such lock-in induces tickets: fiscal transfers. Households in small lots receive the same local public goods as those in large ones, but with a lower property tax burden, creating an incentive to buy the smallest house on the block, which bids up the price of small houses. Our model with exogenous G indicates such transfers are not necessary for the emergence of tickets.

[4]In principle, we cannot rule out a second-order feedback effect through changes in the sorting equilibrium, which may undermine the above logic. As the population characteristics change in $n+1$, land demand may increase enough to increase land prices, and hence feedback on the desire to enter the community, depressing ticket prices. Nevertheless, tickets are still important for clearing the market, even in that case, meaning the consensus view of hedonic pricing is misspecified. We conjecture that the first-order effect dominates and that, in the presence of restrictions on the number of lots, G will be capitalized into tickets, a conjecture ultimately testable in our empirical section.

(1) and (2) are met. (If $\underline{h}$ is not binding at all lots, developers can re-allocate land to increase profits.) Thus, we still have $p_n(h_n) = \beta_n h_n$. That is, our theory predicts minimum lot sizes are the exception to the rule that land-use restrictions can create tickets.

This point may be surprising to some, given the influence of Hamilton (1975), which showed that minimum lot sizes mimic a head tax. However, that paper presents the special case in which the constraint is binding on everybody in a neighborhood, so all housing demands collapse to a single point. As noted above, in that special case, minimum lot sizes are identical to restrictions on the number of housing units. Additionally, since all the housing units collapse to a single point in characteristics space, one could draw any number of hedonic price functions through that single point. Appendix A provides additional details on this point, as well as a model of a household's optimization problem, which clarifies in what sense a minimum purchase requirement is equivalent to a two-part tariff in this case.

Whether β_n increases or decreases in this scenario is an empirical question, even abstracting from any effects of lot size restrictions on amenities such as green space and congestion (Glaeser and Ward (2009), Ihlanfeldt (2007)). On one hand, the restriction per se reduces the utility a household can achieve in the neighborhood, reducing land demand at the extensive margin; on the other hand, by its nature, it requires that more land be consumed by the constrained households, which is equivalent to a reduction in supply faced by the unconstrained households. If neighborhoods are sufficiently different and if a large number of people are at the constraint, we would expect housing prices to increase, as we find in our simulations below.

2.4 Simulations

We illustrate these predictions with policy simulations. We consider a city with two neighborhoods, each with land area fixed at 3,333 units and with $G_1 = 1$ and $G_2 = 1.5$. An outside option (alternative city) is available with a fixed land price at \$12,000 per unit and $G_0 = 0$. We simulate 10,000 households i with utility function,

$$u_i = (1 - \theta_i)\ln(z) + \theta_i \ln(h) + \phi_i G, \tag{4}$$

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

$$v_i = \max_{n,h_n} (1 - \theta_i)\ln(y_i - \alpha_n - \beta_n h_n) + \theta_i \ln(h_n) + \phi_i G_n. \tag{5}$$

In our simulations, we allow heterogeneity in income and tastes, with $y_i \sim \text{u}(40000, 100{,}000)$,

Table 1: Summary Statistics from Simulations

Attribute	Neighborhood	Scenario 1	Scenario 2	Scenario 3
Housing Units	1	3,075	4,037	4,036
	2	6,323	4,416	4,036
Avg Lot Size	1	1.08	0.83	0.83
	2	0.53	0.75	0.82
Price of Land	1	19,956	25,045	19,990
	2	38,713	43,889	21,419
Price of Ticket	1	0	0	6,439
	2	0	0	20,156
Mean Income	1	69,719	60,778	62,432
	2	70,213	79,052	79,229
Mean θ	1	0.31	0.29	0.30
	2	0.29	0.30	0.30
Mean ϕ	1	0.29	0.44	0.46
	2	0.64	0.67	0.69

NOTES: The table displays output from the equilibrium obtained numerically in simulations as described in the main text. Source: Authors' calculations on simulated data.

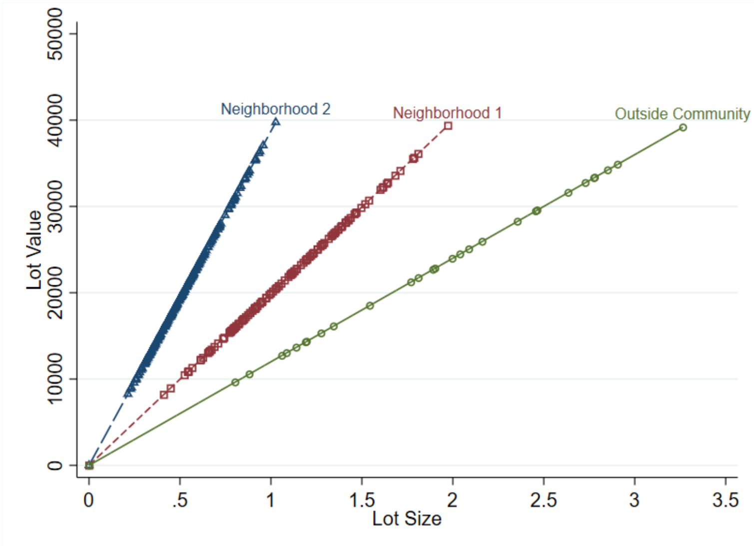
$\theta_i \sim$ u(0.2, 0.4), and $\phi_i \sim$ u(0.1, 0.9).

We consider three different land-use scenarios. In the first scenario, there are no restrictions. In the second, we introduce a minimum lot size in the city (i.e., in $n = 1, 2$) of 0.75 units, designed to bind on some but not all households. In the third, we replace the minimum lot size restriction with a restriction on the maximum number of lots (calibrated to be the same as the number of lots in Neighborhood 1 in the second scenario's equilibrium). Table 1 and Figures 1-3 summarize the outcomes across the three scenarios. In the figures, 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.

Table 1 and Figure 1 show that, in Scenario 1, the price of land is almost twice as high in Neighborhood 2 as in Neighborhood 1 and there are of course no ticket effects. The table also shows that households with higher ϕ (i.e., higher tastes for public goods) sort into the high-G neighborhood, as we would expect. The total number of residents is 9,398, or almost the entire population, with about two-thirds living in the high-G neighborhood.

In Scenario 2, the minimum lot size reduces the total population in the city to 8,453 and especially reduces the density in the high-G neighborhood. Land prices increase in both neighborhoods. Moreover, the heterogeneity in lot sizes decreases, as can be seen in Figure 2 (where the vertical line indicates the minimum lot size), but it does not collapse to zero, with the lot size restriction remaining non-binding on about 35% of households in

Figure 1: 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. Source: Authors' calculations on simulated data.

Neighborhood 1 and 8% of households in Neighborhood 2. (Indeed, average lot size actually falls in Neighborhood 1, as migrants from Neighborhood 2 and the constraint on low-demand types increases the price for unconstrained households.)

Finally, in Scenario 3, we see the introduction of entry tickets, as the extensive margin price is now necessary to satisfy the condition on the number of lots in additional to equimarginality. 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.

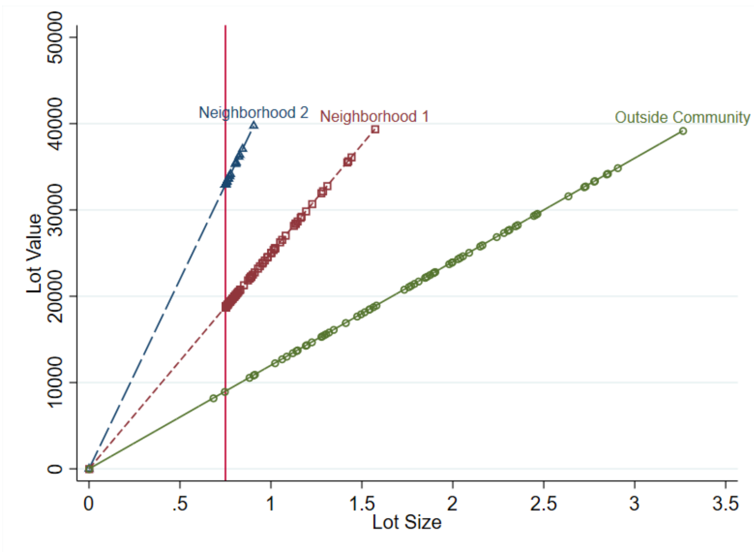
2.5 Housing Structures

For simplicity, we have been allowing land to represent housing services, entering the utility function directly. In this sub-section, we briefly extend the model to show that the intuition still holds when households demand housing services more generally, using land as an input.

Suppose that housing services are produced from land and capital inputs, that land prices continue to have a price at the extensive margin (α) and at the intensive margin ($p_{L,n}$), and that the price of physical capital (bricks, etc.) is constant at p_K. Suppose in particular that housing services are produced according to a CES production function:

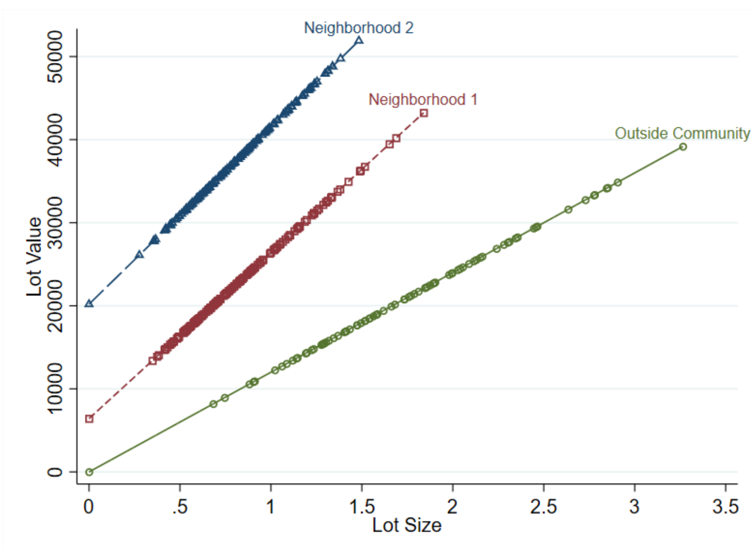
$$h = (L^\rho + K^\rho)^{1/\rho}. \tag{6}$$

Figure 2: Simulation 2: Minimum Lot Size



NOTES: The figure plots housing values to lot size for the simulated equilibrium under a common minimum lot size constraint, depicted by the vertical solid line. Each point represents a housing unit, and lines are drawn for each community, extending through the vertical axis for visual reference. Source: Authors' calculations on simulated data.

Figure 3: Simulation 3: 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. Source: Authors' calculations on simulated data.

Then, by cost-minimization, the cost of producing a house of size h is

$$c(h) = \alpha_n + h \cdot (p_{L,n}^{\rho/(\rho-1)} + p_K^{\rho/(\rho-1)})^{(\rho-1)/\rho}, \tag{7}$$

recognizing that the price must be paid at the extensive margin as well as for construction. In this case, the price function remains linear in housing services h, with the unit price of h increasing in the unit price of land ($p_{L,n}$). Significantly, the model is like the simpler land-only model, with an extensive margin for a housing unit α_n and a unit price of housing services β_n, where $\beta_n = (p_{L,n}^{\rho/(\rho-1)} + p_K^{\rho/(\rho-1)})^{(\rho-1)/\rho}$. The only difference is that those services are produced by a bundle of land and capital.

In practice, of course, we do not observe "housing services" per se, but rather a set of indicators like lot size, living area, and bathrooms, which could have a mixed interpretation as inputs and outputs. Accordingly, in our empirical test of the model, we follow the standard practice of flexibly estimating a housing services function from the observed hedonic variables.

We also acknowledge the possibility that the production function for housing could be more complicated than this CES example, giving rise to non-linearities in h. In general, we cannot non-parametrically identify a non-linear price function of $p(h)$ separably from a non-linear housing services function $h(x)$, a point emphasized by Epple, Quintero, and Sieg (2019) and Landvoigt, Piazzesi, and Schneider (2015). Notably, we do not observe the limit of housing prices as lot sizes or dwelling areas shrink to zero (leaving only tickets). However, our goal is more modest: to characterize how such a composite function varies across neighborhoods with varying G, and how this variability differs by land-use restrictions—namely whether they shift up the whole function by a constant or tilt up the slope on average. Significantly, if what we identify as tickets in our model were driven by construction costs or 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.

3 Data

This section summarizes the data we use to test our theory of how land-use restrictions affect the hedonic equilibrium.

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. The data provider is CoreLogic.[5] 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. CoreLogic provides a unique property identifier that facilitates a merge of the deed transactions to the tax assessment data. The data include detailed spatial information, which allows us to place the properties into local housing markets—typically, metro areas as defined by core-based statistical areas (CBSAs), and then neighborhoods within these markets.[6] Property locations are the latitude and longitude coordinates of the parcel on which the structure sits. 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. This timeframe is driven by the availability of school attendance and performance data, described below.

We focus our analysis on single family homes and therefore exclude multifamily structures.[7] Single family properties are the most common structure type in the U.S. and are more likely to be owner-occupied. But our main reason for doing this is to ensure the property data have a reliable measure of the amount of land occupied by the structure.

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 housing service model. We also exclude outliers with apparently erroneous or highly unusual attribute or price information. Specifically, we exclude 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.

---

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

[6]We break apart the three largest metro areas: New York City into its New York state and New Jersey components, Los Angeles into Los Angeles and Orange counties, and Chicago into Cook County and its surrounding suburban counties.

[7]Specifically, we exclude any property that reports more than two units or fails to report lot size. This rule admits properties that are approximately single family equivalent but may have a second unit available, such as duplexes or "twins," or homes with basement apartments, in-law suites, and the like. We control for the number of units in all property level regressions.

Summary statistics can be found in Appendix Table E1. The table shows the number of properties, transactions, and mean price by city.

Replacement Cost Estimates. One of our model specifications adjusts the value of the property by the replacement value of the structure. Our replacement value estimates come from construction cost summaries provided by RSMeans, a provider of cost estimates to the construction industry. We match these replacement cost estimates to properties by year of transaction and size category.[8]

3.2 Local Amenity Data

We assemble data on local amenity offerings from several sources, beginning with schools, by which we define a property's neighborhood.

Public Schools: Location. We define neighborhoods by their assigned public schools. We choose this definition for two reasons. The first is the importance of school quality to many households and its attention in the literature in urban economics and local public finance. The second is the fine geography of school attendance zones, which 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).

This neighborhood definition requires information on public school assignment, which we obtain from two sources. Most useful are boundary attendance zones maps from the School Attendance Boundary Information Network System (SABINS). Using the SABINS shapefiles and properties' latitude/longitude coordinates, we place each property into its allotted school attendance zone. These data are most complete for the 2009-2010 school year, which drives our sample selection decisions.

The geographic coverage of SABINS is extensive but not comprehensive, and parts of some cities do not have complete maps. For remaining properties without a boundary-defined attendance zone, we use a two-step procedure. First, we place the properties into school districts using maps from the U.S. 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. Table E1 in the data appendix reports how many properties are matched to schools using attendance boundary files versus the district and nearest-school method.

[8] Size categories are defined in 200 square foot bins from 1,200 to 2,200 square feet, plus 2,200-2,600, 2,600-3,200, and above 3,200. The 2,000 square foot category is additionally matched by one and two story structure options. (Smaller properties have one story only and larger have two story only.)

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.[9] Our main metric of school quality is the percent passing fourth grade math proficiency (the earliest widely available grade level). Hence, our school boundaries focus on schools containing a fourth grade class. Math and reading scores are highly correlated, so we adopt one of them as an index of school quality. Because exams may vary between states, we standardize to a z-score within the state, meaning achievement is judged relative to other fourth graders in the state using the same exam. Appendix Table E2 reports the (unstandardized) mean and standard deviation of proficiency scores across neighborhoods in our sample.

Environmental Quality. We use two measures of local environmental quality, air pollution and hazardous waste exposure. For air pollution, we use Environmental Protection Agency (EPA) monitoring data on the number of ozone non-attainment days—that is, the number of days the monitor reported an excess of a safe level of ozone—in the year 2009. For each neighborhood, we linearly interpolate the three closest monitors, weighting by the inverse of the distance.

The second measure is the proximity to toxic waste sites as defined by the EPA's National Priorities List (NPL, often known as "Superfund" sites). We use the count of NPL sites within five kilometers.

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.[10]

Because all the amenities are in different units, we standardize each measure to a z-score for comparison. Appendix Table E2 reports the (unstandardized) mean and standard deviation of environmental quality and urban centrality measures for neighborhoods in our sample.

[9]For schools with small numbers of students taking such exams, the passing proficiency data are reported in intervals, and the smaller the pool of students, the wider the interval. We limit to schools with intervals no larger than 20 percentage points and take the midpoint of the reported interval as the measure of passing proficiency.

[10]For a few cities with multiple large cities, 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 in the metro area.

3.3 Regulations and Frictions

Zoning. Our measure of regulatory stringency is the Wharton Land Use Regulation Index (WRI) from Gyourko, Saiz, and Summers (2008). This has become a standard data set for much of the urban economics literature on zoning. The WRI is based on a survey of local land use planning officials, who are asked about minimum lot sizes, impact fees, time to permit, the prevalence of environmental study requirements, and the like.

The aggregate WRI is a composite of several subcomponents, and Gyourko et al. (2008) provide suggested weights for summarizing the subindices. In our baseline specifications, we use the composite WRI, but additional specifications split out density restrictions from the rest of the composite index using the weights provided by Gyourko et al. (2008).

The survey is conducted at the municipal level (i.e., the city or other political unit issuing permits for construction). In some specifications, we use the raw WRI at the municipal level. However, not every municipality in a metro area is covered by the survey, which in our case leads to a substantial loss of neighborhood data. Gyourko et al. (2008) suggest aggregating to the metro area level, which we do via weighting by the land area of the municipality. Our baseline specification uses the metro level WRI.

All regulation scores are normalized to have mean zero and unit variance within the cities in our sample. Appendix Table E3 includes the average WRI index by metropolitan area and the availability of neighborhoods with covered municipalities.

Historical Development. In addition to *de jure* regulation, we investigate whether existing development creates a *de facto* regulation 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, many years before the transactions in our sample. For this, we use county-level census data. Our preferred metric is 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 E3 includes the average share of old housing by metropolitan area.

3.4 Sample Definition

To summarize, our data cover transactions occurring between 2005 and 2012 for properties with viable attribute information. The properties are in metro areas covered by the WRI and can be placed into school attendance zones by at least one of two mapping methods. Our discrete neighborhood definition is according to the school attendance zone, and the school must have sufficient test score data. All told, we have roughly 17.3 million transactions from

141 metro areas located into neighborhoods.

We recover neighborhood-level pricing functions. If, after the sample selection just described, any neighborhood has fewer than 30 transactions, we group it into a residual neighborhood. Because the residual is an artificial place, it is excluded from regressions that require amenity data.

4 Empirical Model

We test our theory of two-part tariff capitalization by an empirical study of the pricing functions of neighborhoods in our national sample. We approach this task in two stages. First, we recover the implied intercepts and slopes for each neighborhood in each city in the data. Second, we relate these intercepts and slopes to an index of neighborhood amenities to elicit the contribution of tickets to the capitalization function relative to slopes, testing how the contribution varies with market-level frictions to housing provision.

4.1 Two-Stage Model

The first step is to estimate, market by market, the pricing function for each neighborhood. We estimate the following nonlinear model:

$$p_{icn} = [\alpha_{cn} + exp(\beta_{cn} + H_i)]\epsilon_{ic}, \tag{8}$$

where p_{icn} is the observed transaction price of property i in city c and neighborhood n. The ticket price is α_{cn}. Mathematically, it is an intercept (i.e., the price at no housing service), but as such a point is outside the support of the data, it is better interpreted as a parallel shift of the price function. β_{cn} is the slope price, as it determines the rate of increase of price as the property increases in size. Note the α's are in dollars while (the exponent of) the β's are in dollars per unit of housing services.

We take the exponential of housing services because this functional form nests the semilog model: when $\alpha = 0$, $ln(p_{icn}) = \beta_{cn} + H_i$, where the β_{cn} would be neighborhood fixed effects in the semilog model and the H_i is some estimated function of housing services.[11] This restricted model is routinely used in hedonic modeling (e.g. Avenancio-León & Howard, 2022; Banzhaf, 2021). Our generalized functional form also imposes a constraint that prices be non-decreasing in the amount of housing services. Our main results are robust to using a simple linear model without the exponential function (see Appendix B).

[11] Typical notation for a hedonic model with prices p and housing attributes X is $ln(p) = a+bX$. In equation (8), we represent a by β and bX by H.

Note that each parameter is indexed by n, because we recover each of the two parameters for each neighborhood in the data. These thousands of parameters then become the data points for our second stage estimation, which runs the following nonlinear model:

$$\alpha_{cn} = \alpha_c + (1 + \alpha_z Z_c) \cdot \gamma' G_n \tag{9a}$$

$$exp(\beta_{cn}) = \beta_c + (\beta_0 + \beta_z Z_c) \cdot \gamma' G_n. \tag{9b}$$

The second stage model recovers:

(i) An average ticket and slope for each market, respectively, α_c and β_c, to account for differences in price levels across metro areas, the direct effects of city-wide amenities like climate, and the direct effect of zoning and other market frictions previously studied by Glaeser and Gyourko (2003) and others.

(ii) The direct effect of an index of neighborhood-level amenities, $\gamma' G_n$, on tickets and slopes respectively, captured by the first terms in parentheses, 1 and β_0.[12]

(iii) The interaction effect of how housing market frictions in the city, 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 frictions on capitalization by tickets. If tickets are real, then increased frictions in the wider market should lead to more stratification through tickets among neighborhoods. If $\alpha_z > 0$, a higher regulatory index exhibits more capitalization through tickets.

(iv) The index of neighborhood public goods and amenities, $\gamma' G$. However, without quasi-experimental variation, we do not claim that γ represents marginal WTP. We jointly estimate this model with the cross-equation restriction that the γ are the same in the (a) and (b) portions of (9).

(v) The scaling parameter that accounts for the difference in scale between tickets and slopes (values versus value per unit H), β_0.

The summary statistics in Appendix Tables E1 and E3 are organized around these two stages.

[12] 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.

4.2 Housing Services

To estimate the model, we need to specify a housing services index, H_i. We consider seven different possibilities. In three of them, we use the immobile input to housing, land, as the housing service index. Specifically, we set $H_i = ln(L_i)$ but control for non-land housing characteristics separately. These models take the form

$$p_{icn} = [\alpha_{cn} + exp(\beta_{cn} + ln(L_i)) + \lambda_i]\epsilon_{ic},$$

where L_i is the land area occupied by the property and λ_i is a control for structure attributes, where λ can be estimated within the model for tickets and slopes or calibrated beforehand. In this form for housing services, a case with no tickets implies prices are linearly increasing in land area, $p_{icn} = \tilde{\beta}_{cn} L_i + \lambda_i + \epsilon_{ic}$.

In model (i), our most basic approach, we use land only in the model, setting $\lambda = 0$. In model (ii), we account for capital improvement by subtracting the replacement cost of the structure from the value of the home, recovering the residual value of the land. That is $\lambda_i = E(CC_i)$, with CC denoting construction cost. In model (iii), we estimate the structure value within the model. That is, we specify $\lambda_i = \lambda_c' X_i$, where X_i is a vector of controls for 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. In this model, we divide the largest cities into submarkets for tractability.

In the remaining four models, we jointly estimate an index for housing services. These models take the form

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

where $\hat{H}$ is an index of housing services. Model (iv), the simplest of these, uses only living area as the service index. In the others, we estimate a flexible function of housing services in a preliminary step, sampling a nationally-representative subset of data to devise an index of housing service comparable across geographic areas. With this consistent estimate of $\hat{H}_i$, we then estimate the model on the full data set. Model (v) uses land and living area and model (vi) uses land and living area interacted with vintage. Finally, model (vii), the most flexible, uses all the information of lot area, living area, structure age, and room partitions. An issue with this approach is that some areas lack some housing attribute information (room partitioning in particular), which limits the number of metro areas we can accommodate.

5 Results: Regulatory Frictions and the Hedonic Equilibrium

This section reports the main results from estimating equation (9).

5.1 Regulatory Frictions at the Metropolitan Level

Table 2 presents the results from this model using the metro-level regulation index as a measure of zoning. Each column represents a separate regression, each using one of the respective seven measures of housing services H. Within each column, the seven rows represent the estimated coefficients from equation (9). Observations in these regressions are the estimated α_{cn} and β_{cn} from the first stage models, (8). The regression is weighted by the square root of the number of transactions contributing to the first stage estimate. (Appendix Tables B1 and B2 display regressions for alternative weightings and first-stage functional forms.) Homoskedastic standard errors for each coefficient are reported in parentheses.[13]

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 prices, an increase in amenities increases a neighborhood's ticket price.

The second coefficient, β_0, is a scaling coefficient that converts dollars of housing value between intercepts and slopes. This parameter is a technical necessity to depict a housing price function—we use it later to trace out pricing functions–but the results are not readily interpretable across models because the parameter's scale depends on the housing services index used in the model.

The third coefficient, β_Z, is the interaction of the zoning measure with the slope estimates. A positive coefficient indicates that more regulated areas capitalize amenities more into the per-unit cost of housing services; conversely, a negative coefficient would mean less capitalization through slopes. Across models, we find a mix of small positive coefficients and estimated zeros. 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

[13] We have also used standard errors clustered at the neighborhood level, with no material effect on the results.

Table 2: Capitalization Function Regression Model: Metro-Level Zoning

	Land			Housing Services Function			
Specification	Land Only (i)	Replace Cost (ii)	Property Attributes (iii)	Living Area (iv)	Land & Area (v)	Land & Area X YrBlt (vi)	Property Attributes (vii)
α_Z	0.334	0.498	0.273	0.744	0.318	0.376	0.480
	(0.015)	(0.020)	(0.014)	(0.078)	(0.014)	(0.041)	(0.024)
β_0	0.037	0.036	0.029	2.078	0.017	0.481	0.313
	(0.013)	(0.015)	(0.012)	(0.121)	(0.012)	(0.037)	(0.019)
β_Z	0.001	0.014	0.009	0.463	0.001	0.145	0.087
	(0.013)	(0.015)	(0.013)	(0.058)	(0.012)	(0.034)	(0.018)
Test Scores	32.164	23.743	23.985	6.821	33.905	18.817	15.725
	(0.428)	(0.370)	(0.304)	(0.361)	(0.430)	(0.636)	(0.313)
Dist. to CBD	-4.424	-8.266	-7.016	-2.270	-9.879	-4.457	-11.411
	(0.321)	(0.272)	(0.272)	(0.164)	(0.339)	(0.443)	(0.279)
NPL Sites	-9.260	-5.993	-3.641	-1.398	-10.658	-5.707	-0.657
	(0.978)	(0.760)	(0.771)	(0.366)	(1.014)	(1.314)	(0.696)
Ozone Days	-1.723	-1.891	-0.470	-0.591	-1.945	-0.899	-1.982
	(0.327)	(0.257)	(0.270)	(0.125)	(0.335)	(0.436)	(0.236)
Fixed Effects	City	City	Submkt	City	City	City	City
Cities	141	132	141	141	140	140	124
Submarkets			184				
N'hoods	23,014	23,287	22,912	23,063	23,615	23,584	20,962

NOTES: The table reports results from equation (9) using metro-level measures of regulatory frictions and neighborhood-level pricing functions and amenity indices. The data are obtained from first stage estimates according to equation (8), using neighborhood-level observation counts as weights. Source: Authors' calculations using data described in Section 3.

housing service when paying more at the extensive margin for a high-amenity neighborhood.

The last four coefficients compose 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.[14] The coefficients are consistent with intuition: the G index is increasing in test scores and decreasing in distance from jobs and pollution.

Quantitatively, the coefficients in Table 2 are difficult to compare across models because they are interacted with housing service indices of different scale. However, for each model, we can recover the implied dollar value difference between neighborhoods at different values of the G index. Specifically, we compare values, by house size, at the 25th percentile of G (a "base" neighborhood) and at the 75th percentile (a "prime" neighborhood). We begin by finding the premium at the average level of zoning. Using the regression equation, and setting $Z = 0$, the premium can be calculated as

$$\hat{p}_{prime} - \hat{p}_{base} = (1 + \beta_0 H) \times \gamma'(G_{prime} - G_{base})$$

for a given amount of housing services H.[15]

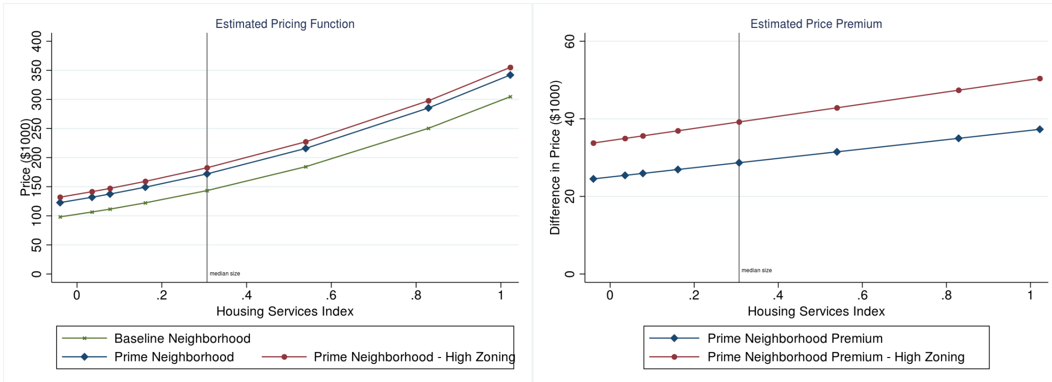
Figure 4 traces out the implied value as housing services increase in the base and prime neighborhoods. For this illustration, we use housing services model (vi), land and living area interacted with structure age. The lefthand panel of the figure plots the pricing functions implied by the model at various percentiles of the housing service distribution, with a vertical line at the median-sized property. The baseline neighborhood is the green line with hatched markings, and the prime neighborhood, average zoning, is the blue line with diamond-shaped markings. A prime neighborhood in a high-zoning market, to be discussed later, is the red line marked with circles.

The figure illustrates the importance of intercepts in the capitalization function–not only that they are nonzero, but they are correlated with neighborhood amenities. The prime neighborhood (blue line) appears to be a parallel shift up of the base neighborhood (green line), with nearly all the capitalization coming via the ticket (extensive margin) price. To focus on the comparison, the righthand panel of the figure takes the *difference* in the projected prices, plotting the premium associated with the prime neighborhood. The premium is relatively constant–while it does grow slightly as homes increase in size, most of it is realized even at the smallest properties–which illustrates that capitalization is primarily through tickets.

[14] We have also experimented with other measures of test scores, air quality, and a crime exposure index. We chose these four to be parsimonious, and results were not materially different with other indices.

[15] To be consistent with the pricing model (8), housing services are exponentiated in the calculation, but we spare the notation here.

Figure 4: The Value of Housing Services



NOTES: The figure reports 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 in Table 2. Source: Authors' calculations using data described in Section 3.

Table 3 presents the numerical values of these premiums. (These results are again based on housing services model (vi), land and living area interacted with structure age. Appendix Table B3 provides results for the other models.) Column 1 shows the point in the housing services distribution at which the premium is evaluated. Column 2 shows the base value at the home's size, and Column 3 shows the premium over this base value when moving from lesser to greater amenities. For example, the median-sized property in the prime neighborhood commands a $28,700 premium over the base neighborhood. Even a very small property (the 1st percentile of sizes in a typical city) is due a $24,500 premium, saving just $4,200 compared with the median-sized property, though its base value (without the prime amenities) is $45,000 less. Column 4 shows the premiums as a percentage of the base value. These values steadily fall as the size of the house increases. Moving a small property from a base neighborhood to a prime neighborhood results in a 25 percent increase in price, but for the largest properties, the proportional increase is half that magnitude. Column 5 shows the share of the premium made up by the ticket. At the median-sized property, the ticket is 87 percent of the overall premium, which diminishes just to 67 percent for a very large home. Together, the premium as a share of home value and the ticket as a share of premium underscore the importance of extensive margin neighborhood pricing.

Figure 4 and Table 3 also show how an increase in the stringency of regulation affects the capitalization function. Generalizing from the previous case where $Z = 0$, the amenity price for a neighborhood in a city with regulation index $Z \neq 0$ is:

$$\hat{p}^{Z}_{prime} - \hat{p}^{Z}_{base} = (1 + \alpha_Z Z + (\beta_0 + \beta_Z Z) \cdot H) \times \gamma'(G_{prime} - G_{base})$$

In Figure 4, the red line marked with circles shows the price of a prime amenity neigh-

Table 3: Capitalization Function Under Metro-Level Zoning

		Average Zoning			High Zoning			
Size Pctile (1)	Base Value (2)	Premium (3)	Premium /Value (4)	Ticket Share (5)	Premium (6)	Premium /Value (7)	Ticket Share (8)	Premium Difference (6)-(3)
1	98,200	24,500	0.250	1.020	33,800	0.344	1.019	9,200
5	106,500	25,400	0.239	0.983	34,900	0.328	0.984	9,500
10	111,500	25,900	0.233	0.964	35,600	0.319	0.966	9,700
25	122,200	26,900	0.220	0.928	36,900	0.302	0.932	10,000
50	143,300	28,700	0.200	0.871	39,200	0.273	0.877	10,500
75	184,300	31,500	0.171	0.794	42,800	0.232	0.803	11,400
90	250,400	35,000	0.140	0.715	47,400	0.189	0.726	12,400
95	304,700	37,300	0.122	0.670	50,400	0.165	0.682	13,100

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 in Table 2, from the Land and Area X (interacted with) Year Built model. Source: Authors' calculations using data described in Section 3.

borhood in a city with regulation one standard deviation above average, or $Z = 1$. The lefthand plot shows the additional zoning shifts the pricing function upward, reflecting the ticket effect of tighter regulation. The righthand plot displays the price premium, the difference relative to the baseline neighborhood, being nearly parallel to the premium in an average regulation city. These show that in more regulated cities, higher amenity neighborhoods are relatively more expensive than lower amenity alternatives, and the premium is of a similar dollar magnitude across the distribution of home sizes. Columns 6 to 8 in Table 3 report the premium in a highly regulated city, and the last column reports the difference in premiums between average and high-zoning cities. At the median-sized home, the high amenity neighborhood in the more regulated city is $10,500 more expensive than the same comparison in a city with average regulations. Nearly 88 percent of this premium comes from a higher ticket price. From the 5th percentile sized home to the 95th, the premium increases $15,500, compared with the rise of $11,900 in the averagely regulated city. The additional regulation results in more dispersion across neighborhoods, and this dispersion is mostly manifested through tickets. Hence, the premium accounts for a higher percentage of the value of a small property, and especially so in a regulated city.

5.2 Regulatory Frictions at the Municipal Level

The metro area regulatory index afforded the inclusion of all neighborhoods within a metropolitan area with available data, as recommended by Gyourko et al. (2008). It is, however, a coarse measure of the actual regulatory regime a neighborhood faces, because it assigns the same stringency index to all areas of a metro area.

Our next specification uses the finer geography available in the WRI, at the Census Place (a village, township, or Census-designated neighborhood of a large city), 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.[16]

Table 4 reports the regression results for the municipal-level regulatory index. The results are similar to the metro-level index. More regulated municipalities capitalize amenities into

[16] A neighborhood is lost from the sample when its Census Place is missing from the WRI survey or when there are insufficient school attendance zones within the municipality to measure a within-municipality variation. For example, a small city with one school zone would be excluded, even if its regulatory stringency is reported in the WRI.

tickets more so than less regulated municipalities ($\alpha_z > 0$), even when comparing among cities *within* the same metro area. Again, the effect on capitalization into the slope of the housing services function (β_z) is positive in most cases, but is small and not significantly different from zero. 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 respective regulatory environments, not simply that more regulated regions tend to have higher housing prices.

5.3 Multiple Dimensions of Regulatory Frictions

Our index of zoning frictions is a composite of multiple dimensions of regulation. However, as discussed in Section 2, despite the literature's focus on minimum lot size, our theory suggests that such restrictions will not induce capitalization into tickets, except in the special case where they also create a binding limit on the number of housing units. Accordingly, we next treat minimum lot size separately from other forms of regulatory restriction.

The WRI survey included a question on whether a minimum lot size is present in the locality, and if so, how large the minimum is set to be. For a stringency index, we use the minimum size lot area, set to zero when no restriction is present, denoted below as M.[17] We then form a new composite regulatory index purged of the lot size component, $\tilde{Z}$, reweighting the other subindices accordingly. We then enter both indices into our second stage regression, interacting each with intercept and slope coefficients.

$$\alpha_{cn} = \alpha_c + (1 + \alpha_z \tilde{Z}_c + \alpha_M M_c) \cdot G_n \tag{10a}$$

$$\beta_{cn} = \beta_c + (\beta_0 + \beta_z \tilde{Z}_c + \beta_M M_c) \cdot G_n. \tag{10b}$$

Table 5 reports the results of this regression using the metro level regulatory indices, and Table 6 reports the results from the municipal level indices. The tables have the same structure as the other regression results. On the regulatory index coefficients, α_z and β_z, the results are very similar to the specifications without lot size: Higher regulatory frictions lead to more capitalization of amenities into tickets, with mixed evidence of the effect on slopes. However, consistent with our theory, the lot size restriction index, represented by α_M and β_M, does not have the same effect. In fact, we estimate it has the opposite effect, leading to *less* capitalization through tickets. These results are consistent with a compensating price

[17]We have also used the binary variable of whether an index is present, with similar results.

Table 4: Capitalization Function Regression Model: Municipal-Level Zoning

	Land			Housing Services Function			
Specification	Land Only (i)	Replace Cost (ii)	Property Attributes (iii)	Living Area (iv)	Land & Area (v)	Land & Area X YrBlt (vi)	Property Attributes (vii)
α_Z	0.098	0.082	0.147	0.154	0.211	0.607	0.291
	(0.018)	(0.020)	(0.018)	(0.122)	(0.019)	(0.172)	(0.031)
β_0	0.045	0.032	0.041	3.697	0.056	2.278	0.387
	(0.020)	(0.022)	(0.021)	(0.517)	(0.020)	(0.370)	(0.033)
β_Z	0.022	0.024	0.029	0.487	-0.011	0.137	0.047
	(0.018)	(0.019)	(0.017)	(0.134)	(0.018)	(0.130)	(0.028)
Test Scores	23.873	18.946	17.986	3.290	23.784	6.056	11.463
	(0.519)	(0.443)	(0.391)	(0.445)	(0.509)	(0.911)	(0.403)
Dist. to CBD	-1.169	-10.197	-8.269	-0.543	-7.562	-4.812	-12.451
	(0.671)	(0.576)	(0.491)	(0.171)	(0.632)	(0.821)	(0.527)
NPL Sites	-14.316	-9.528	-6.935	-1.611	-12.545	-0.511	-2.768
	(2.074)	(1.779)	(1.634)	(0.513)	(1.905)	(1.469)	(1.433)
Ozone Days	-5.327	-6.336	-4.618	-0.917	-6.123	-1.688	-4.129
	(0.603)	(0.516)	(0.435)	(0.184)	(0.559)	(0.486)	(0.443)
Fixed Effects	City	City	City	City	City	City	City
Cities	93	87	93	92	93	92	81
Submarkets			132				
Munis	497	481	479	481	497	495	435
N'hoods	6,338	6,208	6,023	6,244	6,358	6,304	5,221

NOTES: The table reports results from equation (9) using municipal-level measures of regulatory frictions and neighborhood-level pricing functions and amenity indices. The data are obtained from first stage estimates according to equation (8), using neighborhood-level observation counts as weights. Source: Authors' calculations using data described in Section 3.

rationale. If the purchase amount is restricted, and the constraint is binding, the price per unit must be lower to afford the consumer utility equal with his unconstrained optimum. For the slope coefficient, the evidence is again mixed, with some specifications negative and some zero and/or imprecisely estimated. Overall, these results indicate that minimum lot size has been overemphasized in the literature, while other regulatory frictions are important for driving the capitalization function towards extensive margin pricing.

5.4 Historical Frictions

Our theory and the empirical results so far indicate that frictions inhibiting the adjustment of the housing stock can result in capitalization via tickets. Zoning is a measurable and policy-relevant form of friction, but certainly not the only one. We next consider another source: history. Structures are highly durable, lasting decades or longer. 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 (from the developers' perspective), a friction that functions similarly to zoning.

In the following set of results, we substitute an "age of stock" index for the regulatory index used in prior models. We want to be careful to isolate a notion of the extent of development in the past, not simply (the inverse of) recent growth in the housing stock. Thus, 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. (Our data span 2005 to 2015.) We use county as the geographic area for age of stock measurement.

Table 7 reports 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. The one exception is the specification using year built in the housing services model (model (vi)), likely because the housing services model is already embedding much of the variation in the frictions index. 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 insignificant or zero.

Appendix Table B4 reports the implied amenity premium in a typical metro area for the housing stock age model. Ticket capitalization of amenities is apparent for an area of average development history. However, areas more rigid due to historical development exhibit the majority of their amenity capitalization through tickets, which implies a greater share of

Table 5: Capitalization Function Regression Model: Metro-Level Zoning, With Minimum Lot Size

	Land			Housing Services Function			
Specification	Land Only (i)	Replace Cost (ii)	Property Attributes (iii)	Living Area (iv)	Land & Area (v)	Land & Area X YrBlt (vi)	Property Attributes (vii)
α_Z	0.343	0.436	0.265	0.511	0.335	0.297	0.446
	(0.015)	(0.018)	(0.012)	(0.047)	(0.014)	(0.043)	(0.023)
α_{ls}	-0.114	-0.188	-0.098	-0.252	-0.120	-0.062	-0.150
	(0.010)	(0.009)	(0.010)	(0.020)	(0.010)	(0.035)	(0.013)
β_0	0.069	0.054	0.043	1.218	0.008	0.600	0.304
	(0.027)	(0.028)	(0.024)	(0.109)	(0.025)	(0.093)	(0.037)
β_Z	0.011	0.016	0.012	0.309	0.001	0.234	0.089
	(0.012)	(0.013)	(0.011)	(0.038)	(0.011)	(0.041)	(0.016)
β_{ls}	-0.023	-0.018	-0.011	-0.100	0.000	-0.156	-0.045
	(0.013)	(0.014)	(0.012)	(0.035)	(0.012)	(0.041)	(0.018)
Test Scores	41.847	37.101	28.458	13.428	45.948	24.655	22.951
	(1.170)	(1.079)	(0.696)	(0.935)	(1.189)	(1.983)	(0.843)
Dist. to CBD	-6.023	-12.299	-8.563	-4.883	-12.997	-4.804	-15.428
	(0.485)	(0.558)	(0.366)	(0.412)	(0.564)	(0.763)	(0.623)
NPL Sites	-12.424	-9.542	-3.309	-2.475	-15.440	-8.310	-2.411
	(1.387)	(1.314)	(0.878)	(0.752)	(1.450)	(2.094)	(1.042)
Ozone Days	-3.146	-4.019	-0.366	-1.724	-3.620	-1.698	-3.834
	(0.485)	(0.481)	(0.323)	(0.286)	(0.503)	(0.711)	(0.392)
Cities	141	132	141	141	140	140	124
Submarkets			184				
N'hoods	23,116	23,382	22,912	23,228	23,817	23,817	21,154

NOTES: The table reports results from equation (10) using metro-level measures of regulatory frictions and neighborhood-level pricing functions and amenity indices. The data are obtained from first stage estimates according to equation (8), using neighborhood-level observation counts as weights. Source: Authors' calculations using data described in Section 3.

Table 6: Capitalization Function Regression Model: Municipal-Level Zoning, With Minimum Lot Size

	Land			Housing Services Function			
Specification	Land Only (i)	Replace Cost (ii)	Property Attributes (iii)	Living Area (iv)	Land & Area (v)	Land & Area X YrBlt (vi)	Property Attributes (vii)
α_Z	0.141	0.152	0.208	0.482	0.280	0.984	0.403
	(0.021)	(0.023)	(0.021)	(0.152)	(0.022)	(0.268)	(0.036)
α_{ls}	-0.048	-0.143	-0.096	-0.568	-0.052	-0.361	-0.238
	(0.017)	(0.019)	(0.017)	(0.133)	(0.018)	(0.158)	(0.027)
β_0	0.045	0.032	0.042	3.479	0.057	2.715	0.374
	(0.020)	(0.022)	(0.021)	(0.468)	(0.020)	(0.504)	(0.033)
β_Z	0.027	0.032	0.037	0.572	-0.010	0.252	0.060
	(0.020)	(0.022)	(0.020)	(0.148)	(0.020)	(0.178)	(0.031)
β_{ls}	-0.005	-0.009	-0.011	-0.175	-0.018	-0.228	-0.059
	(0.017)	(0.019)	(0.017)	(0.116)	(0.018)	(0.155)	(0.027)
Test Scores	23.824	18.747	17.925	3.452	23.570	5.054	11.053
	(0.518)	(0.441)	(0.390)	(0.447)	(0.507)	(0.890)	(0.393)
Dist. to CBD	-1.444	-10.615	-8.850	-0.867	-7.983	-4.571	-12.972
	(0.673)	(0.578)	(0.493)	(0.196)	(0.633)	(0.861)	(0.529)
NPL Sites	-13.720	-8.971	-6.390	-1.480	-12.354	0.018	-3.305
	(2.064)	(1.740)	(1.636)	(0.519)	(1.886)	(1.241)	(1.397)
Ozone Days	-5.231	-6.496	-4.719	-1.051	-6.230	-1.482	-4.332
	(0.611)	(0.520)	(0.440)	(0.198)	(0.564)	(0.443)	(0.440)
Fixed Effects	City	City	City	City	City	City	City
Cities	93	87	93	92	93	92	81
Submarkets			132				
Munis	497	481	479	481	497	495	435
N'hoods	6,338	6,208	6,023	6,244	6,358	6,304	5,221

NOTES: The table reports results from equation (10) using municipal-level measures of regulatory frictions and neighborhood-level pricing functions and amenity indices. The data are obtained from first stage estimates according to equation (8), using neighborhood-level observation counts as weights. Source: Authors' calculations using data described in Section 3.

Table 7: Capitalization Function Regression Model: Housing Stock Development Age

	Land			Housing Services Function			
Specification	Land Only (i)	Replace Cost (ii)	Property Attributes (iii)	Living Area (iv)	Land & Area (v)	Land & Area X YrBlt (vi)	Property Attributes (vii)
α_Z	0.184	0.365	0.187	0.581	0.127	-0.029	0.386
	(0.012)	(0.014)	(0.010)	(0.045)	(0.011)	(0.031)	(0.016)
β_0	0.039	0.032	0.030	1.687	0.006	0.400	0.287
	(0.012)	(0.013)	(0.010)	(0.078)	(0.011)	(0.034)	(0.016)
β_Z	-0.009	0.008	0.004	0.303	0.042	0.306	0.086
	(0.011)	(0.013)	(0.010)	(0.041)	(0.011)	(0.032)	(0.015)
Test Scores	37.228	29.985	26.430	9.149	40.844	23.900	20.378
	(0.464)	(0.421)	(0.277)	(0.368)	(0.469)	(0.778)	(0.353)
Dist. to CBD	-5.529	-10.951	-8.068	-3.266	-12.372	-4.508	-14.777
	(0.512)	(0.473)	(0.305)	(0.241)	(0.518)	(0.767)	(0.393)
NPL Sites	-15.330	-11.743	-4.423	-2.945	-18.628	-11.531	-4.265
	(1.368)	(1.164)	(0.861)	(0.553)	(1.450)	(2.223)	(1.011)
Ozone Days	-1.274	-2.096	-0.602	-0.867	-1.877	-1.335	-2.809
	(0.509)	(0.455)	(0.068)	(0.210)	(0.518)	(0.769)	(0.380)
Fixed Effects	City	City	Submkt	City	City	City	City
Cities	145	134	145	145	144	144	128
Submarkets	197	186	187	195	196	196	174
N'hoods	23,195	23,418	22,991	23,307	23,896	23,896	21,233

NOTES: The table reports results from equation (9) using county-level measures of historical development and neighborhood-level pricing functions and amenity indices. The data are obtained from first stage estimates according to equation (8), using neighborhood-level observation counts as weights. Source: Authors' calculations using data described in Section 3.

amenity capitalization in the value of small properties.

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

In the previous section, we analyzed the equilibrium hedonic price function and how it capitalizes amenities in the presence of land-use restrictions. Having established that tickets are an important component of the capitalization function, we turn our attention to the implications of this pattern for valuing amenities.

To fix ideas, we begin with a simple illustration of amenity estimation when tickets are more or less important to the underlying capitalization function. Then, we apply our model to an actual school quality valuation exercise.

6.1 The Hedonic Model Under Tickets and Slopes

We begin by generating some intuition using simulations, which assure a controlled environment. We simulate data of the kind that would be seen by an econometrician, with housing services, neighborhood quality, and housing prices. Following the form of equation (8), we draw data according to

$$p_{in} = \alpha_c + \alpha_G G_n + exp(\beta_G G_n + H_i) + \epsilon_i, \tag{11}$$

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.[18] There are two neighborhoods, one normalized to $G = 0$ and the other with high $G = 1$.

We consider three simulations, all of which fix the premium at the median-sized property. 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.[19]

The econometrician observes H, G, and p, and estimates a regression to recover the parameters $\alpha_c, \alpha_G, \beta_G$. We then evaluate the difference it makes when estimating the full

[18] Note this is the model of Section 4, with α_G replacing $(1 + \alpha_z Z)$ and β_G replacing $(\beta_0 + \beta_z Z)$ at some normalized Z.

[19] In all scenarios, the relationship between α, 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 $\alpha = \Delta_{med} exp(1 + H_{med}) - exp((1 + \beta) + H_{med})$.

model above in contrast to the commonly used semilog model:

$$\ln(p_{in}) = \tilde{\beta}_c + \tilde{\beta}_G G_n + H_i + \tilde{\epsilon}_i, \tag{12}$$

which effectively assumes that $\alpha = 0$ and so is misspecified in cases 2 and 3. The point here is to see how this misspecification affects our estimate of the value of an amenity.

Figure 5 presents results from the three simulations, from full slope capitalization (left column), half slope and half ticket capitalization (center), and full ticket capitalization (right). (The figure plots one representative draw from the simulations.) Panel A plots the data, with the high-G location in blue and the low-G location in black. The lines plot the true underlying model without error draws, and the clouds of dots show the prices, with error draws, going into the econometrician's regressions. By design, the high-G location has higher prices than the low-G location. When tickets are not contributing to capitalization, the premium for the high-G neighborhood rises with the amount of housing services–the blue line stretches away from the black line as the graph moves along the horizontal axis. When tickets are contributing more to capitalization, the gap remains more similar across the size distribution. At the extreme of full ticket capitalization, the lines remain a constant distance apart.[20]

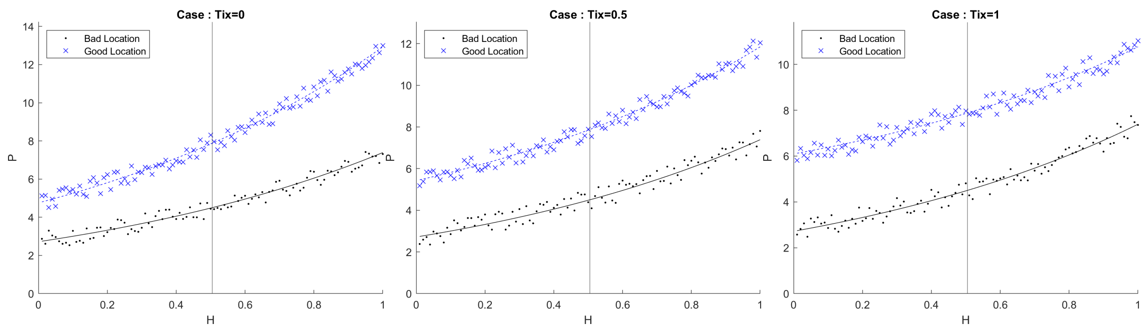
Panel B plots the results from the two regressions (equations 11 and 12), plotting the premium associated with the high-G neighborhood across the housing services distribution obtained from the true model and the semilog hedonic model. In the left column, when tickets are not present, the two models come to the same result and accurately depict the premium for the high-G neighborhood. In the rightmost column, when tickets are the only form of capitalization, the semilog model inaccurately depicts the premium in a particular way. As it results from minimum distance estimation, it can roughly recover the premium at the average level of housing services. However, it incorrectly imposes an upward sloping premium. 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, the average distance between neighborhoods in the middle of the support of h is imposed throughout the distribution of h.

To emphasize this point, Panel C 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

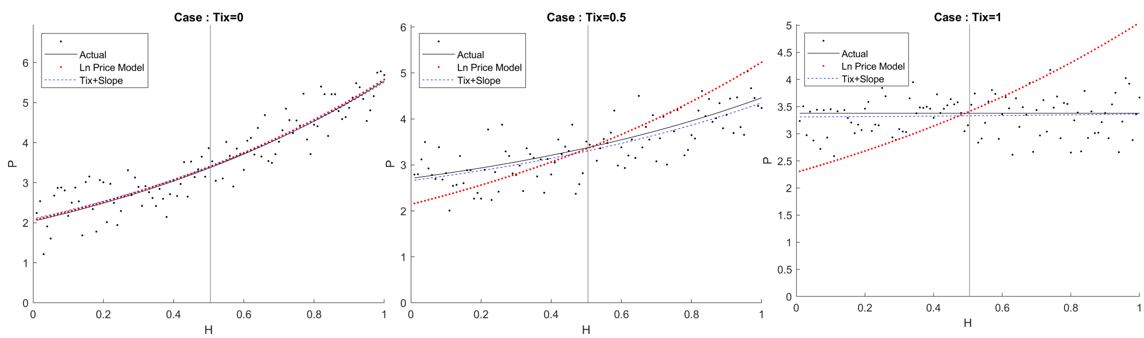
[20] Of course, as noted in Section 2, even in the case of full slope capitalization, the high-G location is more expensive even at the minimum housing services, as H is not literally zero at that level.

Figure 5: Capitalization Via Slopes or Tickets

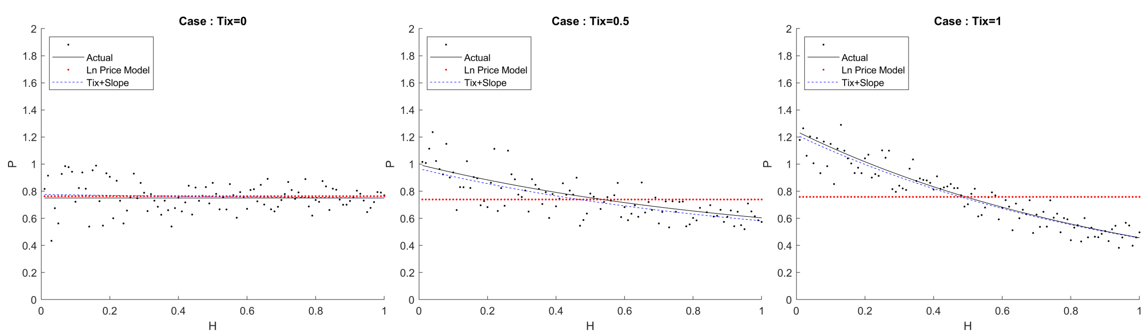
Panel A: Simulated Home Prices



Panel B: Amenity Premium Estimated From Simulated Data



Panel C: 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. Source: Artificial data simulated as described in Section 6.1.

decrease in the home's size, and the semilog model is tilted through the true premium function from the underside.

In the center column, when tickets account for half the capitalization, we see the same qualitative pattern, but the tilt in the semilog model is less severe, simply because tickets are relatively less important.

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, for as we saw in the previous section, ticket capitalization is widespread and substantial.

6.2 Estimating a Hedonic Model With Tickets and Slopes

How can a hedonic model incorporate tickets? First, as usual, the econometrician needs a credible way to isolate quasi-experimental variation in an amenity of interest. In our tests for tickets in Section 5, we noted the models yielded an amenity index, not a measure of WTP for any of its components. With appropriate sample definition, however, our data is suited to a study of WTP for at least one of the amenities: school quality. The neighborhoods in our sample are defined by elementary school attendance zones. Thus, access to a school changes discretely at a boundary, while other amenities vary more continuously from one area to the next. Therefore we can adopt a now-standard method of recovering a WTP estimate, the spatial border discontinuity design pioneered by Black (1999), refined by Bayer et al. (2007) and Kuminoff and Pope (2014), and still widely used (e.g. Zheng, 2022). This design isolates quasi-experimental variation in school quality by narrowing the analysis to a small band around a sharp, discontinuous change in the amenity at the border, controlling for other factors in the region of the discontinuity (which hereafter we denote δ_b).

Second, the econometrician needs to decide on a pricing function to estimate. Equations (1) and (2) tell us only that prices take the form of $p = \alpha(S, \delta_b) + \beta(S, \delta_b, H)$, but not their functional form. We spend the rest of this subsection introducing some approaches.

Semilog Model

The standard semilog version of the boundary discontinuity method is

$$\ln p_{in} = \tilde{\alpha_S} S_n + \tilde{\delta}_b + H_i + \tilde{\epsilon}_i \tag{13}$$

where the amenity of interest, school quality, is S_n, boundary area effects are captured by $\tilde{\delta}_b$, and housing services are denoted H.

Since the semilog model is ticketless, we seek an alternative. The practical challenge with doing so in the boundary design, however, is that the unobserved effects may show up linearly (to capture the capitalization of unobservables into tickets) and nonlinearly (to capture their capitalization into slopes). Thus, there are potentially numerous nuisance parameters. We consider several tractable options. A Monte Carlo analysis of these estimators is reported in Appendix C.

Linear Model

The simplest approach is a linear model

$$p_{inb} = \alpha_0 + \delta_b^\alpha + \alpha_S S_n + \delta_b^\beta H_i + \beta_S S_n H_i + \epsilon_i, \tag{14}$$

where α_S and β_S 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. We assume the expected value of unobservables is continuous at the school boundary, so, after conditioning on the fixed effects, ϵ_i is mean zero.

This model simply interacts the amenity of interest with housing services, including boundary fixed effects *and* housing service interactions.[21] The main advantage of this model is its ease of estimation. Its main disadvantage is that it does not nest the semilog model. In the Monte Carlo simulation in Appendix C, we find that it performs reasonably well even if it is misspecified, exhibiting bias only when ticket capitalization is near zero.

Two-Step Method

The second approach is a two-step estimation routine that assumes the additive-exponential form, as in equations (9) and (11). The model is

$$p_{inb} = \alpha_0 + \delta_b^\alpha + \alpha_S S_n + exp(\delta_b^\beta + \beta_S S_n + H_i) + \epsilon_i, \tag{15}$$

which can be rewritten as

$$p_{inb} = \alpha_0 + \delta_b^\alpha + \alpha_S S_n + exp(\delta_b^\beta) exp(\beta_S S_n) exp(H_i) + \epsilon_i.$$

This expression highlights that the model has effects from unobservables that are both separable and interacted with school quality, unlike the purely linear form in which the slope effects of capitalization are all separable.

[21] We take the exponential of the housing services function to keep closest accord to the model (11), although this is not essential to our point.

The challenge that this model introduces is that it is nonlinear in a large number of ancillary parameters, $\delta_b^\alpha, \delta_b^\beta$. For example, the Los Angeles County and Washington, DC metro areas contain over 1,800 boundary pairs, meaning there are 3,600 ancillary parameters to put into a nonlinear estimation routine.

The two-step procedure splits model (15) into high-dimensional linear and low-dimensional nonlinear pieces, first accounting for area-level amenities (the boundary terms $\delta_b^\alpha, \delta_b^\beta$) and then extracting the capitalization value of the amenity of interest, S. The first stage estimates

$$p_{inb} = \alpha_0 + \bar{\delta}_b^\alpha + \bar{\delta}_b^\beta exp(H_i) + \epsilon_i, \tag{16}$$

which is an analog of (15). The recovered first stage estimates will be a combination of the unobservable/ancillary amenities and the target amenity, which we will decompose in a second step. At the end of this step, we have:

$$\bar{\delta}_b^\alpha = \delta_b^\alpha + \alpha_S(w_1 S_1 + w_2 S_2), \tag{17}$$

and

$$\bar{\delta}_b^\beta = exp(\delta_b^\beta) \cdot (w_1 exp(\beta_S S_1) + w_2 exp(\beta_S S_2)), \tag{18}$$

where w_1, w_2 represent the weights (i.e., the number of observations) assigned to either side (1 or 2) of a school boundary line. Note that school quality S and the weights are observable quantities. Additionally, the nonlinear (exponential) transformation of ϵ_i^β appears in the model. However, by our assumption that all the moments of this distribution are the same on either side of the boundary, this term is absorbed into the boundary fixed effects.[22]

Call the projection of prices from regression (16) $\hat{p}_{inb}$ and the residual $p_{inb}^r = p_{inb} - \hat{p}_{inb}$. The second step uses the residual prices for the following estimator.

[22] For example, if ϵ_i^β is normally distributed on both sides of the boundary with variance σ_β^2, then the first two factors in equation (18) are $exp(\delta_b^\beta)exp(\frac{1}{2}\sigma_\beta^2)$.

$$p^r_{inb} = p_{inb} - \bar{\delta}^\alpha_b - \bar{\delta}^\beta_b exp(H_i) =$$

$$(\delta^\alpha_b + \alpha_S S_n - \bar{\delta}^\alpha_b) + (exp(\delta^\beta_b + \beta_S S_n) - \bar{\delta}^\beta_b) exp(H_i) =$$

$$= \alpha_S S_n - (w_1 \alpha_S S_1 + w_2 \alpha_S S_2) +$$

$$\big[exp(\beta_S S_n) - (w_1 exp(\beta_S S_1) + w_2 exp(\beta_S S_2)\big] exp(\delta^\beta_b) exp(H_i) + \epsilon_i$$

$$= \alpha_S (S_n - (w_1 S_1 + w_2 S_2)) +$$

$$\frac{\big(exp(\beta_S S_n) - (w_1 exp(\beta_S S_1) + w_2 exp(\beta_S S_2)\big)\bar{\delta}^\beta_b}{w_1 exp(\beta_S S_1) + w_2 exp(\beta_S S_2)} exp(H_i) + \epsilon_i \quad (19)$$

which uses the definitions of $\bar{\delta}^\alpha_b, \bar{\delta}^\beta_b$.[23] The second stage is a nonlinear regression, but in just two parameters, α_S, β_S.

Nonparametric Method

The final approach sidesteps issues of functional form by using a nonparametric matching estimator. The idea is to take two properties on either side of a boundary, which implicitly matches them based on wider area-level amenities, and then further pair them based on the similarity of their housing services. In expectation, the difference in their prices would then reflect only the difference in the value of the targeted amenity S.

To see this, consider two properties with the same level of housing services, H, on either side of a boundary. One of these is observed with price p_1 and amenity S_1 and the other with p_2 and amenity S_2. The difference in their prices is

$$\Delta p = \alpha_S (S_2 - S_1) + [exp(\beta_S S_2) - exp(\beta_S S_1)] exp(H), \quad (20)$$

when using the additive-exponential form, as in (15), or its linear form (14),

$$\Delta p = \alpha_S (S_2 - S_1) + \beta_S (S_2 - S_1)] exp(H). \quad (21)$$

After constructing the matching procedure, these are simple regressions recovering two parameters, α_S, β_S.[24] The matching estimator explicitly relies on within-boundary differences in prices. The boundary-level slope pricing is ignored in this approach, as the matching procedure conditions on having the same slope for each pair.

[23] The term $(\bar{\delta}^\beta_b (w_1 exp(\beta_S S_1) + w_2 exp(\beta_S S_2)))^{-1}$ can sometimes be numerically unstable, in which case we set it to one, since it merely scales the slope for all properties in the boundary area by the same factor, and the school valuation is identified off of within-boundary variation.

[24] If the observations are not exactly matched on H, we use the mean of the pair, $\bar{H}$ in the above regressions.

Each of these three options feasibly introduces extensive and intensive margin pricing into a boundary discontinuity research design. *A priori*, we have little reason to believe one is strictly better than another, since each is an approximation to an inherently unknown function. Monte Carlo simulations in which the true data generating process is the additive-exponential (equation 14) indicate that any of the above models can obtain an unbiased estimate of the true capitalization value of a targeted amenity when some ticket capitalization is present, and none suffers from the housing size bias of the semilog model, as depicted in Section 6.1. See Appendix C.

6.3 Application to School Quality Valuation

We use these models to estimate the WTP for an improvement in school quality, taking account of capitalization into tickets as well as into slopes. We do this across our sample of nationwide housing markets.[25] We estimate one metro area at a time, recovering the citywide average WTP implied by each model.

Results for each market are reported in Appendix Tables D1, D2, and D3. The tables show the WTP for a one standard deviation improvement in school quality, for properties at the 25th, 50th, and 75th percentile of size, respectively. Table 8 shows the averages across all markets. Across models and percentiles of the housing distribution, the estimated WTP ranges from about \$3,200 to \$9,000. These figures should be interpreted as present values for an infinite stream of future increases in services. This range compares well 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.[26] Moreover, our models' estimates for the value at a median-sized home in San Francisco range from \$4,200 to \$11,400 (Appendix Table D2), which also is similar to Bayer et al.'s (2007) estimate, although, notably, the ticket-inclusive models are higher and flatter in slope than the semilog model.

The WTP levels differ across models, but the patterns are similar. Notably each model produces a similarly-ordered price premium across markets. Appendix Figure D1 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.

[25] We lose some markets with insufficient coverage in the school attendance zone boundary data, as we need precise geography of attendance boundaries.

[26] Our figure for Bayer et al. (2007) 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 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 (2007), so we can combine their computed ratios with our value from Bayer et al. (2007).

Table 8: WTP For a One Standard Deviation Improvement in School Quality ($1,000)

	Housing Services Quantile		
Model	25^{th}	50^{th}	75^{th}
Semilog	4.757	5.499	6.785
Linear	6.436	7.209	8.489
Nonlinear Two-Step	7.102	7.503	8.380
Matching (NL)	7.677	8.187	9.024
Matching (Lin.)	3.169	3.820	4.790

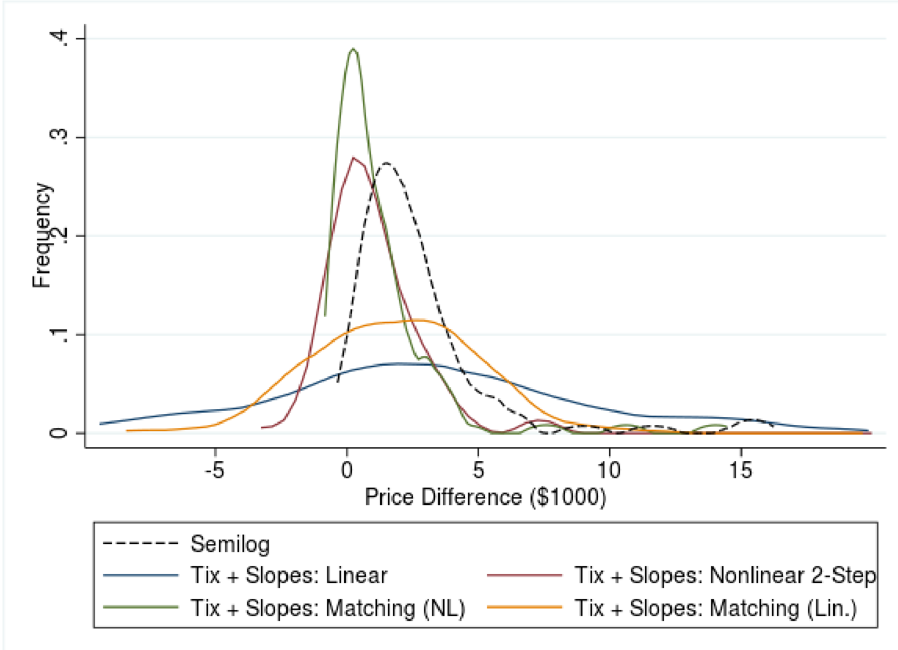
NOTES: The table reports a summary of willingness-to-pay estimates of school quality from the models presented in Section 6.2. Results for each city are available in Appendix D. Source: Authors' calculations using data described in Section 3.

Additionally, in nearly all cases in all models, the estimated WTP increases at higher levels of the housing distribution, as we would expect. But, importantly, this increase is much starker in the semilog model, which forces this result by ignoring tickets. In other models, the increase is more gradual. In the semilog model, a household living in the 75th percentile of house size is estimated to have a WTP 42% greater than a household at the 25th percentile of house size. The premium rises more slowly in models that incorporate tickets; in our preferred nonlinear models, the premium rises only 17% from the 25th to 75th percentile.

This result holds up within cities as well as in these cross-market averages. To see this, we calculate differences in the estimated premium across the housing services distribution within each market, taking the implied WTP for homes of different sizes, and comparing their school quality premia. We do this for each model. Figure 6 plots the distribution (across markets) of the difference between 75th percentile and 25th percentile sized home. Consistent with both the data in Table 8 as well as the simulations in Section 6.1, the standard semilog model imposes the upward slope in a price premium, while tickets allow the premium to be flatter (potentially even downward sloping) in the size of the home. The figure shows the distribution of the 75-25 gap for the semilog model is uniformly positive, larger on average, and narrower in distribution than any of the ticket-inclusive models.

The semilog model imposes a uniform *proportional* price premium. Figure 7 shows the distribution of the difference in the percentage price premium between 75th and 25th percentile sized properties. The semilog model is absent from the plot because it is mechanically zero—properties of all sizes have the same proportional capitalization. The ticket-and-slopes models instead show a disperse distribution of proportional price premia. The vertical lines in the figure represent the upper and lower boundaries of a two-sided t-test. The mass outside the critical area indicates a large fraction of cities have statistically different capitalization rates between large and small properties. This empirical regularity is ruled out by

Figure 6: Difference in Premia Estimates for Large and Small Properties



NOTES: The figure reports the distribution across cities in the difference in estimated willingness-to-pay (in 1,000's of dollars) between a 75th percentile-sized property and a 25th percentile-sized property for the models described in Section 6.2. Source: Authors' calculations using data described in Section 3.

the semilog model.

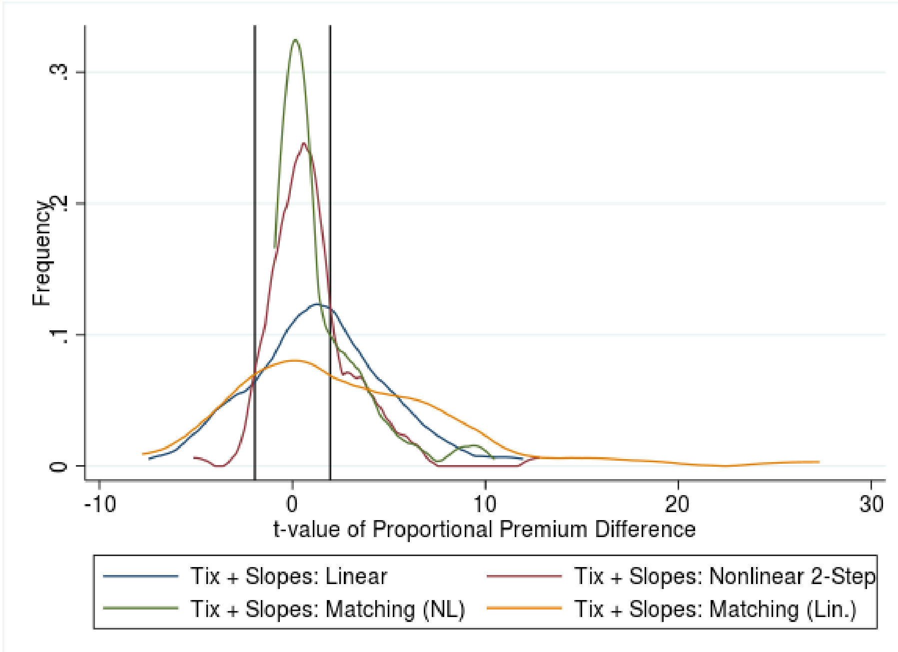
6.4 Implications for Policy Valuation

The previous subsection illustrates that it is possible to conduct hedonic valuation while accounting for the possibility of capitalization of amenities into tickets as well as slopes. It also showed that accounting for tickets substantially shrinks the spread in the estimated heterogeneity of WTP. Or, to put it in other terms, it widens the spread in WTP as a percentage of housing prices, from a constant to a value that falls with house size.

Consequently, accounting for tickets has the potential to have substantial implications for distributional analyses of the benefits of public investments. Intuitively, when using hedonic modelling, accounting for tickets will increase the estimated benefits received by the poor relative to the rich.

Consider the benefits of improving test scores at low-performing schools. In particular, consider increasing test scores by 0.1 standard deviation at schools in the bottom half of the distribution. In partial equilibrium, the properties in affected neighborhoods increase in value according to the estimated premium at their respective property size. We can find total benefits by summing the increase in value across the entire market area and calculate the

Figure 7: Difference in Percentage Premia Estimates for Large and Small Properties



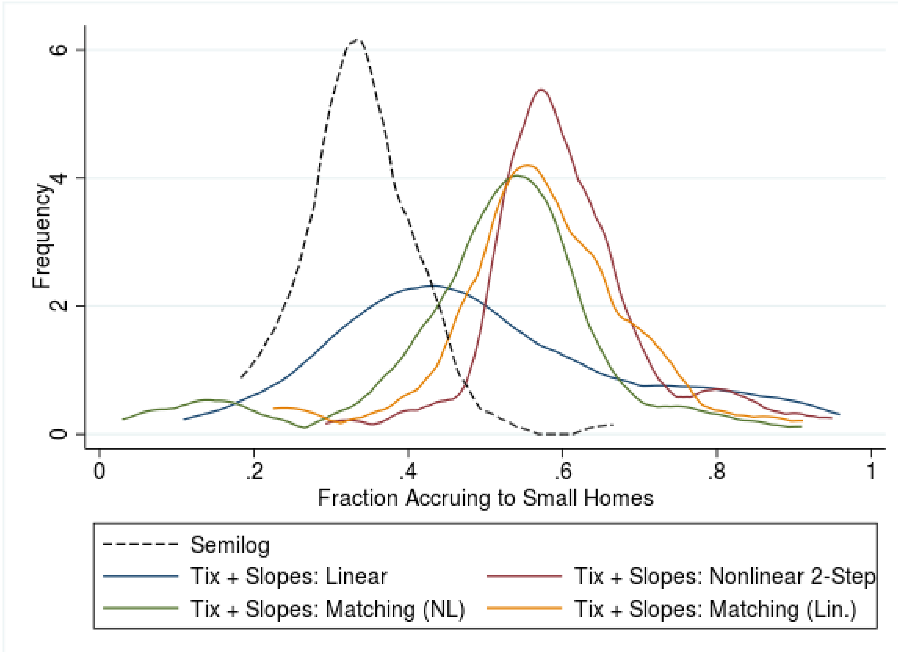
NOTES: The figure reports the distribution across cities in the difference in estimated willingness-to-pay, as a fraction of the home price in an average-amenity neighborhood, between a 75th percentile-sized property and a 25th percentile-sized property for the models described in Section 6.2. Source: Authors' calculations using data described in Section 3.

fraction that accrues to small (below median) size properties. Figure 8 shows the distribution across markets of the fraction of value accruing to small properties following this hypothetical intervention.

When using price premium estimates from the semilog model, the value accruing to small properties displays a fairly narrow distribution centered around 0.35. When using price premium estimates from the ticket-and-slopes models, however, the distribution is on average several percentage points higher, centering around 0.5-0.6. The difference in average is most clear in the nonlinear models.

Thus, the misspecification in the semilog model may cause an understatement of the value of school quality to owners of smaller properties, and by consequence, lead a researcher to understate the distributional implications of such an intervention. The semilog model would say smaller properties owners—on average, households of lesser means—would reap about one third of the value of such a policy intervention, while ticket-accommodating models would say these property owners would reap closer to three-fifths. More fundamentally, however, the ticket model shows residents of smaller properties implicitly place a much higher value on school quality than the semilog model would read from the data, a fact with potentially far-reaching implications for the economics of local public goods.

Figure 8: Fraction of School Intervention Accruing to Small Properties



NOTES: The figure reports 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. Source: Authors' calculations using data described in Section 3.

7 Conclusions

This paper addresses how local public goods are capitalized—whether 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. Importantly, we find empirically that more regulated cities exhibit more capitalization in ticket prices. Hence, regulation seems to amplify a two-part tariff to the capitalization of local amenities. Other frictions based on historical development patterns appear to have the same effect. These findings suggest that ticket price differentiation is under appreciated in the literature.

Our main contribution has been to increase our understanding of 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, it has 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)). Our results are consistent with the notion that zoning creates the ticket price *necessary* for efficient pricing of congested public goods. Nevertheless, we emphasize that the existence of such capitalization is far from 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. Thus, while we cannot pass judgment based on our work alone, we suggest that future work evaluating the normative aspects of spatial sorting should consider two-part pricing. Tickets may approximately deliver per capita pricing and prevent over congestion. Yet, normative evaluations should also consider that tickets price out lower income households who would otherwise be willing to trade housing services for public goods.

Second, our paper suggests that, at least when we are interested in heterogeneous property value impacts, the standard semilog hedonic model may be badly misspecified in the presence of tickets. 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 school quality in poorer, low-value housing areas thus have much greater private benefits to poor households than standard models would suggest.

Third, 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.

References

Avenancio-León, C. F., & Howard, T. (2022). The assessment gap: Racial inequalities in property taxation. *Quarterly Journal of Economics*, *137*(3), 1383-1434.

Banzhaf, H. S. (2014). The market for local public goods. *Case Western Reserve Law Review*, *64*(4), 1441-1480.

Banzhaf, H. S. (2021). Difference-in-differences hedonics. *Journal of Political Economy*, *129*(8), 2385-2414.

Banzhaf, H. S., Ma, L., & Timmins, C. (2019). Environmental justice: The economics of race, place, and pollution. *Journal of Economic Perspectives*, *33*(1), 185–208.

Bayer, P., Ferreira, F., & McMillan, R. (2007). A unified framework for measuring preferences for schools and neighborhoods. *Journal of Political Economy*, *115*(4), 588–638.

Bishop, K. C., Kuminoff, N. V., Banzhaf, H. S., Boyle, K. J., von Gravenitz, K., Pope, J. C., ... Timmins., C. D. (2020). Best practices for using hedonic property value models to measure willingness to pay for environmental quality. *Review of Environmental Economics and Policy*, *14*(2), 260-281.

Black, S. E. (1999). Do better schools matter? Parental valuation of elementary education. *Quarterly Journal of Economics*, *114*(2), 577-599.

Brueckner, J. K. (1981). Zoning and property taxation in a system of local governments: Further analysis. *Urban Studies*, *18*(1), 113–120.

Brueckner, J. K. (2023). Zoning and property taxation revisited—was Hamilton right? *Journal of Urban Economics*, *133*, 103393.

Calabrese, S. M., Epple, D. N., & Romano, R. E. (2011). Inefficiencies from metropolitan political and fiscal decentralization: failures of Tiebout competition. *Review of Economic Studies*, *79*(3), 1081–1111.

Epple, D., Quintero, L., & Sieg, H. (2019). A new approach to estimating hedonic equilibrium models for metropolitan housing markets. *Journal of Political Economy*, *128*(3), 948–983.

Fischel, W. A. (1985). *The Economics of Zoning Laws: A Property Rights Approach to American Land Use Controls*. Baltimore, MD: Johns Hopkins University Press.

Fischel, W. A. (2001). Municipal corporations, homeowners, and the benefit view of the property tax. In W. Oates (Ed.), *Property Tax and Local Public Finance* (p. 33-77).

Glaeser, E. L., & Gyourko, J. (2003). The impact of building restrictions on housing affordability. *FRBNY Economic Policy Review*, 21-39.

Glaeser, E. L., & Gyourko, J. (2018). The economic implications of housing supply. *Journal of Economic Perspectives*, *32*(1), 3-30.

Glaeser, E. L., Gyourko, J., & Saks, R. (2005). Why is Manhattan so expensive? Regulation and the rise in housing prices. *The Journal of Law and Economics*, *48*(2), 331–369.

Glaeser, E. L., & Ward, B. A. (2009). The causes and consequences of land use regulation: Evidence from greater Boston. *Journal of Urban Economics*, *65*(3), 265–278.

Gyourko, J., & Krimmel, J. (2021). The impact of local residential land use restrictions on land values across and within single family housing markets. *Journal of Urban Economics*, *126*, doi.org/10.1016/j.jue.2021.103374.

Gyourko, J., Saiz, A., & Summers, A. (2008). A new measure of the local regulatory environment for housing markets: The Wharton Residential Land Use Regulatory Index. *Urban Studies*, *45*(3), 693-729.

Hamilton, B. W. (1975). Zoning and property taxation in a system of local governments. *Urban Studies*, *12*(2), 205–211.

Hamilton, B. W. (1976). Capitalization of intrajurisdictional differences in local tax prices. *American Economic Review*, *66*(5), 743–753.

Ihlanfeldt, K. R. (2007). The effect of land use regulation on housing and land prices. *Journal of Urban Economics*, *61*(3), 420–435.

Kuminoff, N. V., & Pope, J. C. (2014). Do "capitalization effects" for public goods reveal the public's willingness to pay? *International Economic Review*, *55*(4), 1227–1250.

Kuminoff, N. V., Smith, V. K., & Timmins, C. (2013). The new economics of equilibrium sorting and policy evaluation using housing markets. *Journal of Economic Literature*, *51*(4), 1007–62.

Landvoigt, T., Piazzesi, M., & Schneider, M. (2015). The housing market(s) of San Diego. *American Economic Review*, *105*(4), 1371–1407.

McConnell, V., & Walls, M. (2009). Policy monitor: U.S. experience with transferable development rights. *Review of Environmental Economics and Policy*, *3*(2), 288–303.

Neary, J. P., & Roberts, K. W. (1980). The theory of household behaviour under rationing. *European Economic Review*, *13*(1), 25–42.

Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of Political Economy*, *64*(5), 416–424.

Turner, M. A., Haughwout, A., & Van Der Klaauw, W. (2014). Land use regulation and welfare. *Econometrica*, *82*(4), 1341–1403.

Wilson, R. B. (1993). *Nonlinear Pricing.* New York: Oxford University Press.

Zheng, A. (2022). The valuation of local school quality under school choice. *American Economic Journal: Economic Policy*, *14*(2), 509-537.

Appendices

A Minimum Lot Sizes and the Two-Part Tariff

This appendix clarifies the sense in which minimum lot sizes may induce a two-part tariff, using a model of a constrained household. It uses the same model and notation as Section 2. Conditional on living in neighborhood n, a household maximizes utility subject to the minimum lot size constraint and to a budget constraint on total income y. Ignoring the non-negativity constraint on consumption k, which we assume does not bind, and dropping the household index i, the problem can be written as:

$$\max_{k,h_n} \quad u(k, G_n, h_n) + \lambda(y - k - \beta_n h_n) + \mu(h_n - \underline{h}). \tag{A1}$$

The Kuhn-Tucker conditions pertaining to the household's choice of h are

$$\frac{\partial u}{\partial h} = \lambda \beta_n - \mu, \tag{A2}$$

$$\mu(h_n - \underline{h}) = 0, \quad \mu \geq 0, \quad (h_n - \underline{h}) \geq 0. \tag{A3}$$

For those households for whom the constraint does *not* bind, we have in Condition (A3) $\mu = 0, (\underline{h} - h_n) > 0$. For these households, the situation obviously is identical to the case with no land-use controls. For those households for whom the constraint *does* bind, we have in Condition (A3) $\mu > 0, (\underline{h} - h_n) = 0$. For these households, it is useful to re-write the above constrained optimization problem using the following shadow pricing scheme (Neary and Roberts (1980)):

$$\max_{k,h_n} \quad u(k, G_n, h_n) + \widetilde{\lambda}(y + (\widetilde{\beta_n} - \beta_n)\underline{h} - k - \widetilde{\beta_n} h_n). \tag{A4}$$

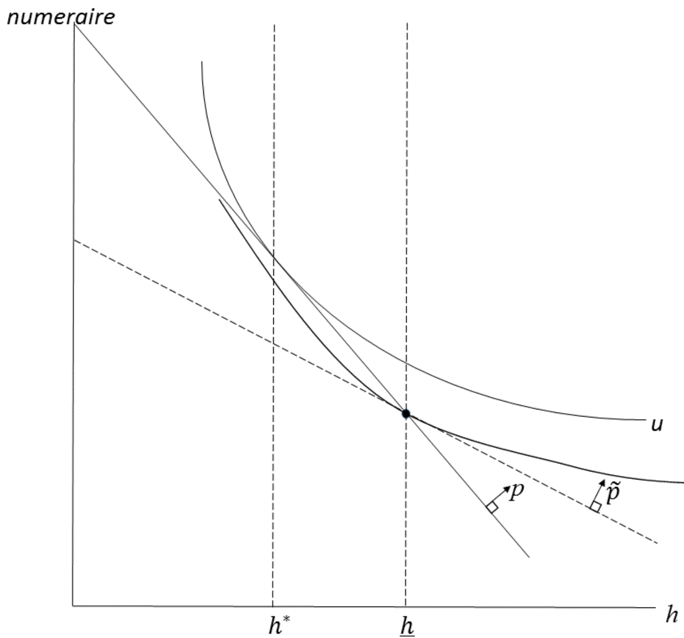
The first-order condition related to the household's choice of h is:

$$\frac{\partial u}{\partial h} = \widetilde{\lambda}\,\widetilde{\beta_n}. \tag{A5}$$

That is, the problem in Expression (A1) where the household *must* buy $\underline{h}$ at a price per square foot of β_n is equivalent to one where it freely chooses to purchase h at a subsidized price per square foot $\widetilde{\beta_n}$ and where "virtual income" is adjusted by the fixed amount $(\widetilde{\beta_n} - \beta_n)\underline{h} \leq 0$ to compensate for the subsidy and leave real income unchanged.[27] To see the equivalency of the problem when the constraint binds, note the first-order conditions (A2) and (A5) are the same if we just let $\widetilde{\lambda} = \lambda$ and $\widetilde{\beta_n} = \beta - \mu/\lambda$. In words, the marginal utility of income

[27] Note that, because $\underline{h}$ is a minimum purchase requirement, we have $\widetilde{\beta_n} < \beta_n$. This is in contrast to the more common rationing constraint in which there is an upper bound on the purchase. In the case of a rationing constraint, the household's problem is equivalent to facing a higher shadow price and an augmented income to cover the additional expenditure and maintain utility. In the case of the minimum purchase requirement, the inequality in the constraint is reversed and so are the sign of the change in the price and the lump-sum adjustment to income.

Figure A1: Optimization with Constraint and with Shadow Values



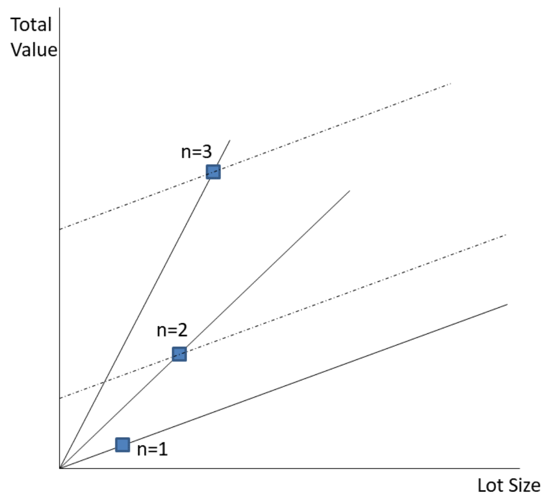
NOTES: The figure displays indifference curves in housing, numeraire space, with household budget constraint for the unconstrained and minimum-purchase constrained scenarios. Source: Authors' illustration.

is unchanged by the combination of a lower price and lower income, and the shadow price per square foot is equivalent to the actual price, adjusted downward by the marginal utility of relaxing the constraint (i.e., μ) converted into dollar units by λ. As the problems are equivalent, the consumer chooses $h = \underline{h}$. Figure A1 compares the primal and dual problems. Given prices p, an unconstrained household would choose h^* and achieve utility level u. The constraint requires the household to consume at least $\underline{h}$, creating a wedge between the slopes of p and the indifference curve, of course lowering utility. However, there is a lower price $\widetilde{p}$ supporting the indifference curve at that point. With that lower price (and with income adjusted down to maintain this lower utility level), the consumer would freely choose $\underline{h}$.

This dual shadow-pricing formulation of the problem is instructive because it clarifies how a minimum purchase requirement can be viewed as equivalent to a two-part tariff (Wilson (1993)). Because $\widetilde{\beta_n} < \beta$, the price function becomes less steep. But income also is adjusted, with the budget constraint shifted downward by $(\widetilde{\beta_n} - \beta_n)\underline{h}$, conditional on choosing the community. Note this is equivalent to paying a fixed fee $\alpha_n = (\widetilde{\beta_n} - \beta_n)\underline{h}$ to enter the community followed by a lower price per square foot. However, while this mimics a two-part tariff on particular households, the equilibrium pricing function does not require a ticket to ration access to the neighborhood. That is, the per-unit land price alone can still clear the market.

This individual-level analysis also clarifies in what sense the minimum lot sizes in Hamilton (1975) induce a head tax. In that paper, Hamilton presents a special case in which the constraint is (just) binding on everybody in a neighborhood, so all housing demands collapse to a single point (see also Brueckner, 1981). In that case, households can be modeled as maximizing utility subject to a two-part tariff, as in Expression (A4), but they also can

Figure A2: Pricing Under Hamilton (1975)



NOTES: The figure displays the value of a home as a function of its lot size under slopes-only capitalization (lines through the origin) and ticket-inclusive capitalization (lines intersecting the vertical axis above the origin). Different lines correspond to neighborhoods with different pricing functions. Source: Authors' illustration.

be modeled as being subject to a standard price, as in Expression (A1). Both are valid, because either price function is consistent with a single data point. Figure A2 illustrates this situation, with three communities each with homogeneous lot sizes. The solid lines fit the data, but so do the dashed lines, which all have the same slope but different tickets. Hence, one can characterize the difference in neighborhood housing prices either with land prices or with tickets. In the more general case where the constraint binds for only some households in the neighborhood, the equivalence is still there for those who are constrained but not for the unconstrained households. Thus, if we are to assume everybody in the community faces the same price function, then there are no tickets into the community. Consequently, the price function continues to take the same form as the case with no land-use restrictions, and G continues to be capitalized into prices, though the values of β_n will differ. In other words, minimum lot sizes can be thought of as inducing a two-part tariff on constrained households, but not on the community as a whole (unless they are binding on everybody).

B Additional Specifications of the Hedonic Equilibrium

This appendix provides additional analyses for the models in Section 5.1.

B.1 Alternative Two-Step Regressions

First, we provide sensitivity analysis for the regressions recovering the capitalization function in the presence of zoning. The main results in Section 5.1 used the nonlinear model (8) and weighted all observations in the second stage by the square root of observations contributing to the first stage neighborhood estimate. This allowed for neighborhoods with the slope term at the numerical boundary approaching $exp(-\infty) = 0$ to contribute in the second stage. Tables B1 and B2 use linear first stage models instead. Table B1 shows results when we weight by the inverse of the variance in the first-stage estimates, while Table B2 alternatively weights by the square root of the neighborhood transactions, as with the nonlinear models. The results are not qualitatively sensitive to these alternatives.

Table B1: Capitalization Function Regression Model: Metro-Level Zoning, Linear First Stage with Standard Error Weights

	Land		Housing Services Function			
Specification	Land Only (i)	Property Attributes (iii)	Living Area (iv)	Land & Area (v)	Land & Area X YrBlt (vi)	Property Attributes (vii)
α_Z	0.270	0.422	1.790	0.471	0.485	0.477
	(0.013)	(0.019)	(0.437)	(0.037)	(0.067)	(0.026)
β_0	0.021	0.020	9.062	1.734	2.943	0.342
	(0.013)	(0.015)	(1.657)	(0.058)	(0.161)	(0.022)
β_Z	0.003	0.005	2.477	0.393	0.640	0.096
	(0.013)	(0.015)	(0.490)	(0.032)	(0.064)	(0.021)
Test Scores	29.077	18.136	1.836	11.977	12.187	12.468
	(0.347)	(0.299)	(0.333)	(0.344)	(0.630)	(0.263)
Dist. to CBD	-5.369	-10.259	-0.318	-2.920	-4.986	-7.708
	(0.272)	(0.243)	(0.064)	(0.159)	(0.303)	(0.230)
NPL Sites	-8.781	-3.870	-0.744	-3.759	-2.914	-1.400
	(0.958)	(0.731)	(0.170)	(0.483)	(0.643)	(0.628)
Ozone Days	-0.662	-1.770	-0.137	-0.651	-1.209	-1.523
	(0.281)	(0.231)	(0.039)	(0.145)	(0.186)	(0.204)
Fixed Effects	City	City	City	City	City	City
Cities	141	141	141	140	140	124
Submarkets						
N'hoods	23,728	23,794	23,569	23,615	23,583	20,952

NOTES: The table reports results from equation (9) using metropolitan-level measures of regulatory frictions and neighborhood-level pricing functions and amenity indices. The data are obtained from first stage estimates according to a linear version of equation (8), without the exponential function on housing services. The second stage uses the inverse variance of the first stage estimates as weights. Source: Authors' calculations using data described in Section 3.

Table B2: Capitalization Function Regression Model: Metro-Level Zoning, Linear First Stage with Neighborhood Size Weights

	Land		Housing Services Function			
Specification	Land Only (i)	Property Attributes (iii)	Living Area (iv)	Land & Area (v)	Land & Area X YrBlt (vi)	Property Attributes (vii)
α_Z	0.342	0.522	1.846	0.724	0.572	0.452
	(0.018)	(0.027)	(0.432)	(0.050)	(0.064)	(0.025)
β_0	0.040	0.046	5.995	1.363	2.153	0.227
	(0.015)	(0.020)	(1.060)	(0.057)	(0.112)	(0.020)
β_Z	-0.002	0.008	1.443	0.281	0.436	0.068
	(0.015)	(0.020)	(0.307)	(0.035)	(0.051)	(0.020)
Test Scores	36.180	22.684	2.666	14.470	16.544	19.928
	(0.558)	(0.484)	(0.465)	(0.492)	(0.789)	(0.422)
Dist. to CBD	-6.385	-12.811	-0.516	-4.402	-6.567	-12.747
	(0.427)	(0.395)	(0.106)	(0.250)	(0.395)	(0.367)
NPL Sites	-11.103	-5.536	-0.922	-4.445	-4.234	-3.525
	(1.297)	(1.030)	(0.240)	(0.652)	(0.834)	(0.954)
Ozone Days	-3.143	-4.005	-0.267	-1.538	-1.790	-2.824
	(0.431)	(0.352)	(0.075)	(0.218)	(0.280)	(0.324)
Fixed Effects	City	City	City	City	City	City
Cities	141	141	141	140	140	124
Submarkets						
N'hoods	23,728	23,794	23,569	23,615	23,583	20,952

NOTES: The table reports results from equation (9) using metropolitan-level measures of regulatory frictions and neighborhood-level pricing functions and amenity indices. The data are obtained from first stage estimates according to a linear version of equation (8), without the exponential function on housing services. The second stage uses neighborhood-level observation counts as weights. Source: Authors' calculations using data described in Section 3.

B.2 Additional Results on the Capitalization Function

Table B3 reports 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 3, in which the results were based only on housing services model (vi), land and living area interacted with structure age. Appendix Table B3 provides results for the other models.

Table B4 reports the implied amenity premium in a typical metro area for the housing stock age model. Again, ticket capitalization of amenities is apparent for an area of average development history (the median of the index share developed by 1970 as of 1980). Though the value of a home in a baseline neighborhood more than doubles from the 5th percentile size to the 95th, the premium in the high amenity neighborhood increases less than 10 percent. The premium increases the value of a small property 51.8 percent when the property moves from a baseline to high amenity neighborhood, but the premium increase is just 28.7 percent for large properties. In older, more-distantly developed areas, the premium for a high-amenity neighborhood is $7,000 higher for the smallest properties, and this additional premium increases to only $11,700 for the largest properties. Hence, areas more rigid due to historical development exhibit the majority of their amenity capitalization through tickets, which implies a greater share of amenity capitalization in the value of small properties.

Table B3: Capitalization Function Under Metro-Level Zoning: Additional Models

			Average Zoning			High Zoning			
	Size Pctile (1)	Base Value ($ 1000) (2)	Premium ($ 1000) (3)	Ticket Share (4)	Premium /Value (5)	Premium ($ 1000) (6)	Ticket Share (7)	Premium /Value (8)	Premium Difference (6)-(3)
Land Only									
Land	25	159.3	45.6	0.935	0.286	59.9	0.949	0.376	14.3
Only	50	170.1	46.1	0.924	0.271	60.4	0.940	0.355	14.3
	75	192.8	46.9	0.908	0.243	61.3	0.927	0.318	14.4
Replace	25	525.9	34.1	0.937	0.065	50.8	0.942	0.097	16.7
Cost	50	529.5	34.5	0.927	0.065	51.4	0.932	0.097	16.9
	75	536.7	35.1	0.911	0.065	52.2	0.917	0.097	17.1
Property	25	59.6	33.5	0.949	0.562	42.7	0.948	0.716	9.2
Attributes	50	63.5	33.8	0.940	0.533	43.1	0.939	0.679	9.3
	75	70.7	34.3	0.927	0.485	43.7	0.925	0.618	9.4
Housing Services									
Living	25	121.6	13.0	0.703	0.107	20.7	0.771	0.170	7.7
Area	50	148.6	17.8	0.513	0.120	26.5	0.601	0.179	8.7
	75	188.3	23.1	0.395	0.123	33.1	0.482	0.176	9.9
Property	25	213.6	33.4	0.720	0.156	47.5	0.749	0.223	14.1
Attributes	50	357.0	38.5	0.625	0.108	54.0	0.659	0.151	15.5
	75	829.8	45.8	0.525	0.055	63.4	0.561	0.076	17.6
Land &	25	134.8	45.5	0.995	0.337	59.9	0.996	0.444	14.4
Area	50	149.4	45.7	0.990	0.306	60.1	0.992	0.402	14.4
	75	180.3	46.1	0.982	0.256	60.5	0.986	0.335	14.4
Land &	25	122.2	26.9	0.928	0.220	36.9	0.932	0.302	10.0
Area X	50	143.3	28.7	0.871	0.200	39.2	0.877	0.273	10.5
Yr Blt.	75	184.3	31.5	0.794	0.171	42.8	0.803	0.232	11.4

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. Source: Authors' calculations using data described in Section 3.

Table B4: Capitalization Function Under Housing Stock Age Index

			Average Stock Age			Older Stock			
	Size Pctile (1)	Base Value ($ 1000) (2)	Premium ($ 1000) (3)	Ticket Share (4)	Premium /Value (5)	Premium ($ 1000) (6)	Ticket Share (7)	Premium /Value (8)	Premium Difference (6)-(3)
Land Only									
Land	25	159.1	52.9	0.933	0.332	61.1	0.956	0.384	8.2
Only	50	169.9	53.5	0.921	0.315	61.6	0.948	0.362	8.0
	75	192.5	54.5	0.905	0.283	62.3	0.937	0.324	7.8
Replace	25	526.0	43.1	0.943	0.082	58.6	0.948	0.111	15.4
Cost	50	529.5	43.6	0.934	0.082	59.1	0.939	0.112	15.5
	75	536.6	44.2	0.920	0.082	59.9	0.926	0.112	15.7
Property	25	76.0	36.9	0.947	0.486	43.7	0.950	0.575	6.8
Attributes	50	82.1	37.3	0.938	0.454	44.1	0.941	0.537	6.8
	75	93.8	37.8	0.925	0.403	44.7	0.928	0.477	6.9
Housing Services									
Living	25	121.6	16.7	0.744	0.137	24.7	0.796	0.203	8.0
Area	50	148.6	22.0	0.565	0.148	30.9	0.635	0.208	8.9
	75	188.3	27.9	0.446	0.148	37.9	0.519	0.201	10.0
Property	25	213.6	42.4	0.737	0.199	57.8	0.749	0.271	15.4
Attributes	50	357.0	48.5	0.645	0.136	65.7	0.660	0.184	17.2
	75	829.8	57.3	0.546	0.069	77.1	0.562	0.093	19.8
Land &	25	134.8	55.1	0.998	0.409	62.8	0.987	0.466	7.7
Area	50	149.4	55.2	0.996	0.370	63.7	0.974	0.426	8.4
	75	180.3	55.4	0.993	0.307	64.9	0.956	0.360	9.5
Land &	25	122.2	34.0	0.939	0.278	34.6	0.895	0.283	0.7
Area X	50	143.3	35.8	0.891	0.250	37.9	0.818	0.264	2.1
Yr Blt.	75	184.3	38.8	0.823	0.210	43.1	0.718	0.234	4.3

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. Source: Authors' calculations using data described in Section 3.

C Monte Carlo Results for Hedonic Estimators

This appendix reports on Monte Carlo simulations designed to evaluate the estimators proposed in Section 6.2, when including boundary fixed effects in our regression discontinuity designed. We compare the performance of the semilog model to other hedonic estimators that allow for ticket capitalization but relax the exact functional form in the interest of computational ease. As a benchmark, we will estimate the "brute force" nonlinear model.

C.1 Simulation Design

To retain tractability for a large scale Monte Carlo simulation, we will work with a relatively small example: eight neighborhoods and four boundaries. Each neighborhood has 200 observed transactions, with the housing services index ranging from zero to one in equal-sized increments. All neighborhoods have the same support of the housing services size distribution.

The Monte Carlo simulation draws 10,000 simulated data sets, from a data generating process that follows equation (14) in the text. The neighborhood qualities are drawn randomly from a uniform interval $s \in [-1, 1]$. We also draw boundary-geography amenity shocks, the ticket-level shocks δ_b^α from a standard normal distribution, and slope-level shocks δ_b^β from a uniform $[0, 1]$ distribution. Idiosyncratic property-level shocks are also drawn from standard normal and uniform distributions, respectively, for ticket and slope forms of pricing. The model has a constant strictly greater than zero. We report here a version of the simulation in which the ticket and slope components of capitalization are uncorrelated (except for s), but we have experimented with many forms of simulation and found similar results throughout. Note, however, that all versions of these estimators rely on the validity of the boundary discontinuity design. If s is correlated with some unobserved neighborhood-level amenities besides the boundary pricing–a failure of the underlying research design–then all estimators considered here are biased.

The simulations run through five scenarios of capitalization, from zero to full capitalization of s via tickets in fractional increments of 0.25. Each version holds fixed the size of the premium at the median value of housing services ($h = 0.5$) between a property in a $s = 1$ neighborhood relative to a $s = 0$ neighborhood. This design allows us to compare how the estimators perform in cases of relatively more or less capitalization in tickets vis-a-vis slopes.

C.2 Results of the Monte Carlo Simulation

In addition to the semilog model and the full nonlinear model, our simulations consider the estimators described in 6.2: two forms of linear estimators, the two-step nonlinear procedure, and nonlinear and linear versions of the matching/nonparametric estimator.

Table C1 reports the results from the Monte Carlo simulation. The numbers in the table report the difference of the model's estimator of the amenity premium to the true premium in the data generating process. Each column corresponds to a different estimator. Each row denotes a simulation with varying degrees of ticket capitalization. The panels correspond to the estimated premia at three levels of housing service; first the median, and then the 25^{th} and the 75^{th} percentiles.

The first result of note is that the semilog model performs poorly in nearly all cases. When the model has any ticket capitalization, the semilog model is biased upwards to an increasing degree in the amount of housing services. For example, at 75 percent ticket capitalization, the median bias in the semilog model is 0.38 at the 25^{th} percentile of housing service, 0.57 at the median, and 0.77 at the 75^{th} percentile. Even with no ticket capitalization in s, the semilog model performs poorly. In Table C1, the simulation with ticket capitalization of zero shows downward biasing of worsening degree in the property size. We have found this is because of the functional form. When the data generating process for prices has *any* additive terms–including a constant or property-level unobservable quality errors—the semilog model exhibits some bias. Unsurprisingly, in simulations where we suppress all linear/additive terms, the semilog model performs very well, but so do its alternatives.

The full nonlinear ("brute force") model naturally performs the best. It achieves negligible bias at all property sizes in all simulation types. When feasible, this model is preferred because of its flexibility and robustness to many forms of capitalization. However, it may not be feasible in many cases of a research design that controls for unobservable factors.

The remaining columns report on the success of the more feasible estimators in achieving the amenity premia of the true data generating process. When there is full ticket capitalization, each estimator performs very well, with no substantial bias at any property size. When there is zero ticket capitalization, the approximating models begin to fail with varying degree of severity. This is because, in finite samples with estimators that in some way rely on minimizing differences from the conditional means, the models are attributing some capitalization to mean differences between neighborhoods. Of these, the two step nonlinear and matching nonlinear estimators have the smallest bias (at least for our simulations, in which the data generating process is nonlinear).

For the more empirically-relevant cases in which capitalization is substantial but not complete (rows with ticket fractions of 0.25-0.75), the approximating estimators perform reasonably well, especially in the nonlinear cases (columns 5 and 6). These have fairly small bias, and notably, they lack the property-size bias profile that is inherent to the semilog model. For example, the two step nonlinear model at 0.75 percent ticket capitalization is every bit as good as the full nonlinear model, and it is much simpler to estimate on a large data set.

The Monte Carlo results, combined with our experience in implementing these estimators at a large scale in real-world data, lead us to prefer the nonlinear estimators and recommend them to researchers interested in accommodating ticket capitalization into hedonic studies of non-marketed amenities.

Table C1: Monte Carlo Simulations For Ticket-Accommodating Estimators of the Boundary Discontinuity Method

Ticket Share	Semilog	Full NL	Linear in $exp(H)$	Two-Step NL	Matching NL	Matching Linear
Median Bias						
At median H						
0.00	0.082	-0.010	0.205	-0.031	0.047	-0.136
0.25	0.217	-0.009	0.178	-0.018	0.033	-0.088
0.50	0.334	-0.011	0.134	-0.014	0.015	-0.053
0.75	0.424	-0.015	0.079	-0.016	-0.001	-0.030
1.00	0.462	-0.022	0.000	-0.025	-0.022	-0.031
At P25 H						
0.00	0.036	-0.015	0.187	-0.003	0.027	-0.118
0.25	0.087	-0.016	0.158	-0.003	0.013	-0.085
0.50	0.124	-0.022	0.115	-0.012	-0.003	-0.059
0.75	0.141	-0.029	0.061	-0.023	-0.018	-0.043
1.00	0.118	-0.040	-0.018	-0.043	-0.038	-0.045
At P75 H						
0.00	0.151	-0.001	0.234	-0.064	0.069	-0.155
0.25	0.401	0.002	0.206	-0.034	0.058	-0.090
0.50	0.628	0.004	0.162	-0.013	0.041	-0.046
0.75	0.818	0.001	0.108	-0.003	0.022	-0.015
1.00	0.932	-0.006	0.026	-0.009	-0.005	-0.015

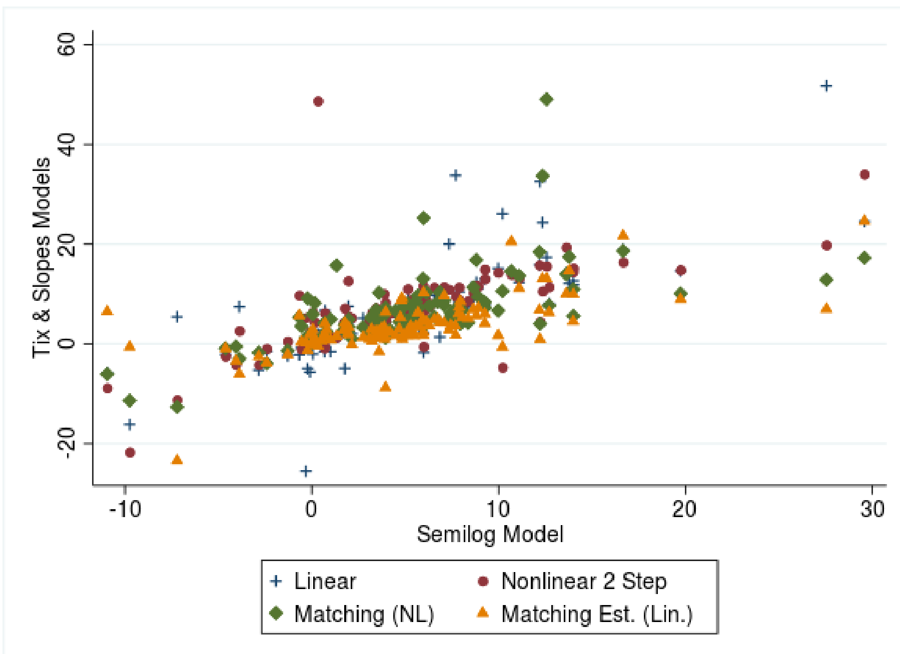
NOTES: The table reports the median difference between the estimated and actual amenity premium for the estimators denoted by column name. The simulated data were drawn from a model according to equation (14). “Full NL” refers to an estimator of the actual model, while the remaining columns refer to the models proposed in Section 6.2. Source: Authors’ calculations using artificial data.

D Summaries of Hedonic Estimates

Section 6.2 presented several approaches for incorporating tickets into hedonic estimators. Figure D1 shows results from the semilog model of Section 6.3 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.

Tables D1 to D3 provide WTP estimates for school quality from our boundary regression discontinuity model. Table D1 reports the WTP estimates for properties at the 25th percentile of the home size distribution for each model in each market with school boundary data. Table D2 reports the same at the median home size, and Table D3 at the 75th percentile. The distribution of estimates is summarized in the main text in Table 8.

Figure D1: Comparison of Premium Estimates Between Hedonic Models: Semilog Versus Tickets and Slopes



NOTES: The figure plots the ticket-accommodating models, as described in Section 6.2, against the semilog model in their estimates of willingness to pay for a one standard deviation increase in school performance. Each dot corresponds to a unique market (metro area) for the model denoted in the legend. Source: Authors' calculations using data described in Section 3.

Table D1: Willingness to Pay (\$1,000): 25^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Akron (OH)	2.94	4.38	2.52	4.84	2.82
Albuquerque (NM)	4.15	5.76	5.17	4.50	3.26
Asheville (NC)	10.14	29.09	9.68	28.63	12.26
Atlanta (GA)	4.28	7.96	10.70	7.19	2.01
Augusta (GA)	6.68	27.82	8.20	7.16	1.70
Austin (TX)	4.25	4.08	9.14	4.88	1.98
Bakersfield (CA)	3.23	4.03	3.72	3.24	2.03
Baltimore (MD)	7.39	7.07	8.17	4.21	3.53
Baton Rouge (LA)	-8.39	-20.71	-24.27	-11.27	0.55
Birmingham (AL)	4.24	3.75	0.68	3.12	9.29
Boise City (ID)	1.53	-1.94	7.51	3.79	2.68
Boulder (CO)	10.32	12.47	13.62	18.58	7.23
Bradenton (FL)	0.56	5.79	5.99	3.74	1.77
Charleston (SC)	-0.19	2.12	0.77	9.28	-3.65
Charlotte (NC)	5.88	11.58	11.02	7.15	7.83
Chicago (Cook) (IL)	3.29	2.54	3.60	9.66	1.92
Chicagoland (IL)	9.47	12.41	13.05	12.91	10.33
Chico (CA)	3.67	3.98	6.47	124.79	3.99
Cincinnati (OH)	10.94	10.92	14.60	44.80	13.45
Colorado Springs (CO)	6.38	26.55	9.64	5.07	2.15
Columbia (SC)	3.93	3.24	5.40	6.41	2.86
Columbus (OH)	2.93	3.66	5.60	5.53	0.71
Corpus Christi (TX)	2.94	2.75	6.95	6.11	-0.65
Corvallis (OR)	3.50	3.48	7.48	1.19	-7.17
Dallas (TX)	3.33	2.55	7.28	6.45	1.55
Deltona (FL)	-0.26	-25.65	5.36	1.25	2.11
Denver (CO)	7.63	9.49	11.73	15.45	3.37
Des Moines (IA)	-0.04	-0.83	0.16	0.17	0.29

Continued on next page

Table D1: Willingness to Pay ($1,000): 25^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Detroit (MI)	0.04	0.40	0.12	0.20	0.70
Dover (DE)	8.99	29.99	-4.39	9.83	5.75
Duluth (MN)	9.58	13.08	13.86	14.61	20.97
Durham (NC)	0.28	1.76	36.81	0.41	0.32
El Paso (TX)	3.20	3.14	4.80	4.17	-0.09
Eugene (OR)	-0.59	3.76	9.57	5.09	2.05
Fayetteville (NC)	5.03	8.12	10.74	11.35	0.65
Fort Wayne (IN)	1.19	1.42	1.03	14.34	1.32
Fresno (CA)	2.69	0.76	4.88	2.01	0.16
Gainesville (FL)	-8.93	-14.75	-9.67	-6.24	7.49
Grand Junction (CO)	-2.12	-3.55	-1.38	-3.92	-2.27
Greensboro (NC)	3.22	2.30	3.35	2.75	0.35
Greenville (SC)	7.48	7.67	10.95	8.42	4.62
Hartford (CT)	12.66	8.36	13.22	10.85	3.46
Houston (TX)	2.98	4.05	4.99	5.81	-0.82
Huntsville (AL)	0.14	2.32	3.85	7.05	-0.55
Jacksonville (FL)	7.46	8.15	15.36	8.47	5.00
Kansas City (MO)	2.44	5.06	3.55	3.04	0.15
Knoxville (TN)	5.46	7.59	11.01	5.04	3.26
Lakeland (FL)	0.57	2.39	-1.08	4.06	1.17
Las Vegas (NV)	-0.09	-8.33	2.19	1.64	0.39
Lexington (KY)	16.74	11.93	14.54	9.54	10.01
Lincoln (NE)	5.00	4.02	3.66	7.29	1.87
Little Rock (AR)	7.52	9.14	9.68	10.48	4.81
Los Angeles (LAC) (CA)	1.81	3.15	3.10	3.09	0.80
Los Angeles (OC) (CA)	11.81	22.59	18.55	14.08	12.85
Madison (WI)	6.99	8.37	8.48	6.94	6.09
McAllen (TX)	-2.44	-2.17	-4.11	-1.70	-2.53

Continued on next page

Table D1: Willingness to Pay ($1,000): 25^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Medford (OR)	3.52	2.68	4.27	2.82	4.13
Memphis (TN)	6.35	3.31	5.98	6.04	4.42
Miami (FL)	8.26	13.49	13.86	5.89	1.64
Milwaukee (WI)	4.36	3.09	5.98	4.90	1.32
Minneapolis (MN)	4.78	8.67	6.41	6.36	-0.04
Mobile (AL)	-3.99	-2.49	-2.25	-1.73	-1.40
Myrtle Beach (SC)	-6.29	8.91	-10.79	-12.53	-31.69
Naples (FL)	22.14	54.29	19.12	12.89	4.93
Nashville (TN)	5.44	9.57	7.29	7.76	5.31
New Haven (CT)	12.76	8.05	9.92	16.24	13.70
New York City (NY)	40.16	88.36	66.41	55.38	15.26
New York City (NJ)	1.89	0.97	4.11	1.01	0.88
Ogden (UT)	6.97	5.93	7.16	5.82	4.69
Oklahoma City (OK)	4.84	7.06	8.67	8.44	4.21
Omaha (NE)	0.47	-0.19	1.38	1.07	-0.07
Orlando (FL)	3.73	6.89	6.91	6.13	-0.02
Ventura (CA)	24.99	30.13	32.87	17.31	12.34
Melbourne (FL)	-1.05	-3.01	0.79	-1.40	-1.94
Panama City (FL)	11.67	6.51	15.17	5.59	7.04
Pensacola (FL)	2.83	-2.53	3.15	2.91	-1.54
Philadelphia (PA)	5.44	4.19	7.87	9.33	3.06
Phoenix (AZ)	4.63	8.17	8.81	4.27	2.96
Pittsburgh (PA)	11.41	7.01	11.24	7.68	6.39
Portland (OR)	4.81	7.06	6.46	5.04	2.22
Provo-Orem (UT)	1.53	2.25	4.55	2.84	1.47
Racine (WI)	-3.77	-4.68	-4.37	-0.49	-3.51
Raleigh (NC)	-0.46	0.41	-1.99	3.70	2.30
Reno (NV)	8.13	9.77	13.31	7.11	6.75

Continued on next page

Table D1: Willingness to Pay ($1,000): 25^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Richmond (VA)	3.28	3.45	10.52	5.41	1.36
Riverside (CA)	1.70	2.43	5.61	4.67	2.28
Roanoke (VA)	1.73	4.63	9.83	2.42	2.67
Sacramento (CA)	3.69	3.47	6.23	2.67	1.54
St. Louis (MO)	9.91	20.31	5.31	3.87	1.77
Salem (OR)	3.19	4.06	3.92	1.70	1.58
Salt Lake City (UT)	5.51	6.16	6.45	3.47	2.55
San Antonio (TX)	0.68	0.16	2.25	2.13	0.63
San Diego (CA)	6.98	8.03	11.12	6.55	6.90
San Francisco (CA)	6.27	8.18	10.71	8.23	3.58
San Jose (CA)	15.26	11.37	15.07	18.15	20.81
Savannah (GA)	4.11	9.36	6.58	5.04	8.59
Seattle (WA)	3.39	2.34	4.29	5.63	-0.05
Stockton (CA)	4.85	3.24	5.09	7.95	3.86
Tampa-St. Pete. (FL)	5.72	-0.45	10.77	9.75	2.84
Tucson (AZ)	0.05	-2.45	6.57	6.03	4.29
Tulsa (OK)	0.60	-2.62	-0.38	1.82	2.24
Norfolk (VA)	6.88	4.66	7.36	6.59	5.04
Visalia (CA)	5.24	4.78	9.37	4.66	2.68
Washington (DC)	4.57	7.32	5.83	4.24	2.01
Wichita (KS)	0.87	-2.95	1.37	4.36	1.07
Wilmington (NC)	-3.28	9.06	2.93	-2.93	1.00
Winston (NC)	5.59	12.92	10.42	7.30	3.68
Worcester (MA)	7.41	5.45	7.35	3.99	8.25
Youngstown (OH)	4.99	-4.31	-0.30	25.22	11.25

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

Table D2: Willingness to Pay ($1,000): 50^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Akron (OH)	3.19	3.93	2.70	5.10	2.94
Albuquerque (NM)	4.68	5.79	5.38	4.41	3.00
Asheville (NC)	12.36	24.37	10.59	33.69	13.08
Atlanta (GA)	5.15	9.07	11.04	8.10	2.73
Augusta (GA)	7.71	33.80	9.51	7.10	1.75
Austin (TX)	4.85	6.20	8.70	5.32	0.96
Bakersfield (CA)	3.76	4.39	3.75	3.27	3.07
Baltimore (MD)	8.37	7.43	8.65	4.24	5.11
Baton Rouge (LA)	-9.75	-16.17	-21.74	-11.38	-0.59
Birmingham (AL)	4.78	3.80	1.44	3.11	8.71
Boise City (ID)	1.77	-4.96	7.15	3.81	4.18
Boulder (CO)	12.19	15.83	15.79	18.44	6.79
Bradenton (FL)	0.70	6.71	6.20	4.23	4.14
Charleston (SC)	-0.23	-4.99	1.62	9.14	-1.29
Charlotte (NC)	7.09	9.28	11.19	7.75	9.68
Chicago (Cook) (IL)	3.60	3.22	3.64	10.25	2.59
Chicagoland (IL)	11.10	12.30	13.21	13.66	11.15
Chico (CA)	4.18	3.93	6.29	137.88	3.61
Cincinnati (OH)	12.57	17.37	15.58	49.08	13.07
Colorado Springs (CO)	7.35	20.03	10.90	4.99	2.78
Columbia (SC)	4.75	4.24	5.72	6.88	5.33
Columbus (OH)	3.23	2.61	6.19	5.49	0.51
Corpus Christi (TX)	3.44	6.14	7.23	6.84	2.52
Corvallis (OR)	3.95	6.00	8.28	1.19	-8.78
Dallas (TX)	3.95	3.38	6.92	7.25	2.47
Deltona (FL)	-0.31	-25.53	5.24	1.23	0.24
Denver (CO)	8.81	12.31	11.73	16.81	5.67
Des Moines (IA)	-0.04	-0.47	0.33	0.17	-0.09

Continued on next page

Table D2: Willingness to Pay ($1,000): 50^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Detroit (MI)	0.04	0.06	0.12	0.18	0.33
Dover (DE)	10.21	26.08	-4.71	10.59	-0.60
Duluth (MN)	10.69	14.54	13.93	14.56	20.54
Durham (NC)	0.33	1.93	48.74	0.41	-0.39
El Paso (TX)	3.61	4.36	4.70	4.44	1.60
Eugene (OR)	-0.67	-2.19	9.73	5.36	5.65
Fayetteville (NC)	5.96	10.72	11.63	13.06	5.00
Fort Wayne (IN)	1.33	1.50	1.27	15.73	1.51
Fresno (CA)	3.07	3.30	4.66	2.08	1.01
Gainesville (FL)	-10.95	-5.81	-8.86	-6.06	6.49
Grand Junction (CO)	-2.41	-1.54	-0.98	-3.93	-3.84
Greensboro (NC)	3.93	1.89	4.00	2.75	1.45
Greenville (SC)	8.92	11.09	11.57	9.42	7.20
Hartford (CT)	14.00	12.67	14.43	10.94	4.53
Houston (TX)	3.54	5.57	4.91	6.47	1.22
Huntsville (AL)	0.16	2.82	4.35	8.20	1.14
Jacksonville (FL)	9.26	13.04	14.95	8.34	4.13
Kansas City (MO)	2.75	5.14	3.42	3.30	1.33
Knoxville (TN)	6.56	9.77	11.34	5.42	4.87
Lakeland (FL)	0.68	0.51	-0.85	4.06	1.94
Las Vegas (NV)	-0.10	-5.66	2.43	1.95	1.93
Lexington (KY)	19.75	14.62	14.83	10.09	8.95
Lincoln (NE)	5.72	3.54	3.88	7.20	3.64
Little Rock (AR)	8.65	9.40	10.28	11.34	6.94
Los Angeles (LAC) (CA)	1.96	3.90	3.22	3.40	1.91
Los Angeles (OC) (CA)	13.63	14.21	19.37	13.98	10.03
Madison (WI)	7.85	8.30	8.99	6.85	6.11
McAllen (TX)	-2.83	-5.26	-4.21	-1.75	-2.50

Continued on next page

Table D2: Willingness to Pay ($1,000): 50^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Medford (OR)	3.96	4.03	4.57	2.83	6.42
Memphis (TN)	7.44	5.25	6.03	6.17	3.67
Miami (FL)	9.98	15.12	14.32	6.69	1.70
Milwaukee (WI)	4.84	5.11	6.36	5.07	1.42
Minneapolis (MN)	5.49	6.48	6.39	6.95	1.67
Mobile (AL)	-4.62	-2.15	-2.48	-0.89	-0.95
Myrtle Beach (SC)	-7.21	5.43	-11.22	-12.66	-23.40
Naples (FL)	27.56	51.76	19.81	12.86	7.00
Nashville (TN)	6.29	8.35	7.40	7.62	3.67
New Haven (CT)	13.78	12.15	10.41	17.46	14.64
New York City (NY)	45.61	92.68	66.93	57.99	25.44
New York City (NJ)	2.15	2.03	5.21	1.05	-0.11
Ogden (UT)	7.68	6.28	7.09	5.83	3.64
Oklahoma City (OK)	5.68	9.56	8.63	9.70	6.24
Omaha (NE)	0.53	0.37	1.35	1.10	0.64
Orlando (FL)	4.48	6.95	6.67	6.64	1.69
Ventura (CA)	29.59	24.57	34.04	17.25	24.65
Melbourne (FL)	-1.29	-2.38	0.51	-1.38	-2.22
Panama City (FL)	14.01	11.83	15.16	5.59	9.94
Pensacola (FL)	3.60	3.02	3.49	3.27	-1.53
Philadelphia (PA)	6.13	7.64	8.69	10.30	4.46
Phoenix (AZ)	5.30	6.73	8.85	4.62	3.57
Pittsburgh (PA)	12.71	8.12	11.43	7.69	6.32
Portland (OR)	5.38	8.31	6.92	5.48	2.63
Provo-Orem (UT)	1.70	2.16	4.22	2.74	2.74
Racine (WI)	-4.06	-4.01	-4.22	-0.52	-3.43
Raleigh (NC)	-0.55	-0.80	-1.07	3.56	0.41
Reno (NV)	9.27	7.81	13.02	7.23	6.02

Continued on next page

Table D2: Willingness to Pay ($1,000): 50^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Richmond (VA)	3.88	4.59	10.03	6.49	3.35
Riverside (CA)	1.98	1.87	5.49	4.89	3.31
Roanoke (VA)	1.95	7.52	12.64	2.48	2.08
Sacramento (CA)	4.19	5.34	6.12	2.77	2.37
St. Louis (MO)	12.22	32.57	4.46	4.02	0.93
Salem (OR)	3.51	3.14	4.12	1.81	1.96
Salt Lake City (UT)	5.98	6.39	6.40	3.44	2.38
San Antonio (TX)	0.80	1.05	2.03	2.48	2.82
San Diego (CA)	7.88	10.44	11.34	7.03	7.37
San Francisco (CA)	7.08	10.48	11.43	8.69	4.25
San Jose (CA)	16.67	18.92	16.39	18.65	21.68
Savannah (GA)	4.83	7.18	6.72	5.07	9.20
Seattle (WA)	3.91	3.14	4.64	5.94	0.99
Stockton (CA)	5.57	5.14	5.07	8.39	3.46
Tampa-St. Pete. (FL)	6.86	1.35	10.68	10.35	4.31
Tucson (AZ)	0.05	-2.05	6.32	5.94	2.86
Tulsa (OK)	0.69	-1.59	-0.35	1.90	1.43
Norfolk (VA)	8.05	7.15	7.73	6.73	5.33
Visalia (CA)	5.98	2.22	9.12	4.58	1.72
Washington (DC)	5.14	7.73	6.39	4.50	1.71
Wichita (KS)	1.01	-1.57	1.46	4.92	0.77
Wilmington (NC)	-3.87	7.45	2.63	-2.98	-6.05
Winston (NC)	6.74	10.69	10.80	8.40	4.98
Worcester (MA)	7.96	7.40	7.81	4.00	8.56
Youngstown (OH)	5.99	-1.74	-0.54	25.25	10.27

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

Table D3: Willingness to Pay ($1,000): 75^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Akron (OH)	3.62	3.20	3.04	5.54	3.12
Albuquerque (NM)	5.54	5.84	5.78	4.28	2.65
Asheville (NC)	16.43	16.00	12.63	42.66	14.25
Atlanta (GA)	6.58	10.89	11.83	9.60	3.68
Augusta (GA)	9.54	43.85	12.30	6.99	1.83
Austin (TX)	5.83	9.57	7.76	6.02	-0.48
Bakersfield (CA)	4.59	4.93	3.82	3.31	4.44
Baltimore (MD)	10.03	8.02	9.66	4.29	7.41
Baton Rouge (LA)	-12.35	-7.58	-15.64	-11.60	-2.40
Birmingham (AL)	5.79	3.90	3.20	3.09	7.79
Boise City (ID)	2.18	-9.93	6.35	3.85	6.32
Boulder (CO)	15.17	21.11	20.70	18.22	6.21
Bradenton (FL)	0.94	8.12	6.58	5.00	7.14
Charleston (SC)	-0.30	-17.81	3.53	8.89	2.24
Charlotte (NC)	9.41	4.95	11.63	8.88	12.48
Chicago (Cook) (IL)	4.19	4.52	3.75	11.36	3.74
Chicagoland (IL)	13.76	12.12	13.54	14.85	12.28
Chico (CA)	4.93	3.86	5.98	156.64	3.13
Cincinnati (OH)	15.15	26.93	17.54	55.42	12.58
Colorado Springs (CO)	8.67	11.34	13.08	4.89	3.52
Columbia (SC)	6.22	5.98	6.40	7.69	8.90
Columbus (OH)	3.70	1.03	7.27	5.44	0.24
Corpus Christi (TX)	4.23	11.30	7.75	7.95	6.72
Corvallis (OR)	4.73	10.31	10.10	1.17	-11.18
Dallas (TX)	5.20	4.98	5.96	8.80	3.95
Deltona (FL)	-0.40	-25.36	5.05	1.21	-2.06
Denver (CO)	10.63	16.61	11.74	18.87	8.66
Des Moines (IA)	-0.05	0.19	0.68	0.19	-0.71

Continued on next page

Table D3: Willingness to Pay ($1,000): 75^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Detroit (MI)	0.05	-0.42	0.11	0.16	-0.18
Dover (DE)	11.84	21.04	-5.24	11.57	-7.96
Duluth (MN)	12.47	16.82	14.06	14.48	19.94
Durham (NC)	0.43	2.26	76.41	0.42	-1.50
El Paso (TX)	4.37	6.49	4.47	4.93	4.21
Eugene (OR)	-0.78	-11.20	10.01	5.75	10.50
Fayetteville (NC)	7.53	14.96	13.28	15.84	11.06
Fort Wayne (IN)	1.55	1.64	1.72	17.94	1.77
Fresno (CA)	3.71	7.39	4.24	2.19	2.20
Gainesville (FL)	-14.26	8.17	-7.34	-5.79	5.19
Grand Junction (CO)	-2.80	1.23	-0.31	-3.95	-5.75
Greensboro (NC)	5.35	1.09	5.64	2.74	3.14
Greenville (SC)	11.39	16.92	12.93	11.11	10.78
Hartford (CT)	16.75	21.44	17.70	11.11	6.44
Houston (TX)	4.38	7.84	4.74	7.45	3.80
Huntsville (AL)	0.21	3.78	5.60	10.42	3.78
Jacksonville (FL)	12.31	20.61	14.15	8.15	2.99
Kansas City (MO)	3.37	5.30	3.09	3.83	3.32
Knoxville (TN)	8.69	13.93	12.13	6.15	7.34
Lakeland (FL)	0.85	-1.96	-0.49	4.07	2.81
Las Vegas (NV)	-0.12	-0.95	2.96	2.50	4.26
Lexington (KY)	25.74	19.87	15.54	11.17	7.25
Lincoln (NE)	6.97	2.73	4.36	7.05	6.22
Little Rock (AR)	10.64	9.86	11.56	12.83	10.07
Los Angeles (LAC) (CA)	2.20	5.04	3.45	3.89	3.45
Los Angeles (OC) (CA)	16.98	-1.05	21.49	13.80	5.70
Madison (WI)	9.01	8.20	9.80	6.74	6.13
McAllen (TX)	-3.53	-10.44	-4.41	-1.83	-2.45

Continued on next page

Table D3: Willingness to Pay ($1,000): 75^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Medford (OR)	4.67	6.14	5.15	2.85	9.63
Memphis (TN)	9.88	9.51	6.18	6.43	2.33
Miami (FL)	13.26	18.11	15.33	8.14	1.78
Milwaukee (WI)	5.58	8.14	7.11	5.33	1.55
Minneapolis (MN)	6.78	2.56	6.35	7.99	4.32
Mobile (AL)	-5.61	-1.63	-2.92	0.39	-0.33
Myrtle Beach (SC)	-8.86	-0.60	-12.13	-12.88	-10.81
Naples (FL)	37.29	47.60	21.19	12.82	9.86
Nashville (TN)	7.81	6.19	7.65	7.37	1.22
New Haven (CT)	15.87	20.39	11.69	19.91	16.34
New York City (NY)	55.89	100.91	68.32	62.95	41.71
New York City (NJ)	2.45	3.20	6.90	1.08	-1.10
Ogden (UT)	8.72	6.79	6.97	5.83	2.28
Oklahoma City (OK)	7.30	14.24	8.54	12.07	9.42
Omaha (NE)	0.62	1.29	1.30	1.14	1.66
Orlando (FL)	5.76	7.05	6.20	7.47	4.04
Ventura (CA)	36.62	16.38	36.45	17.17	40.17
Melbourne (FL)	-1.66	-1.43	0.01	-1.35	-2.57
Panama City (FL)	17.80	19.95	15.14	5.60	13.74
Pensacola (FL)	4.85	11.24	4.09	3.80	-1.51
Philadelphia (PA)	7.71	15.54	11.08	12.53	7.14
Phoenix (AZ)	6.51	4.19	8.95	5.23	4.49
Pittsburgh (PA)	14.95	9.99	11.82	7.71	6.23
Portland (OR)	6.39	10.49	7.97	6.25	3.24
Provo-Orem (UT)	1.99	2.03	3.42	2.58	4.53
Racine (WI)	-4.52	-2.97	-3.93	-0.58	-3.32
Raleigh (NC)	-0.72	-2.92	1.08	3.30	-2.28
Reno (NV)	11.29	4.34	12.36	7.42	4.93

Continued on next page

Table D3: Willingness to Pay ($1,000): 75^{th} Percentile Housing Services

City	Log Price	Linear	NL 2-Step	Matching: NL	Matching: Linear
Richmond (VA)	4.86	6.45	8.93	8.26	6.02
Riverside (CA)	2.52	0.78	5.17	5.32	5.01
Roanoke (VA)	2.26	11.47	17.42	2.56	1.36
Sacramento (CA)	5.10	8.71	5.88	2.94	3.68
St. Louis (MO)	16.01	52.01	2.57	4.25	-0.16
Salem (OR)	4.09	1.51	4.55	1.99	2.55
Salt Lake City (UT)	6.72	6.75	6.29	3.39	2.13
San Antonio (TX)	0.99	2.53	1.53	3.07	5.91
San Diego (CA)	9.39	14.36	11.81	7.80	8.04
San Francisco (CA)	8.41	14.20	12.93	9.43	5.22
San Jose (CA)	18.76	29.89	18.81	19.38	22.84
Savannah (GA)	6.54	2.14	7.08	5.12	10.34
Seattle (WA)	4.66	4.28	5.30	6.37	2.26
Stockton (CA)	6.70	7.95	5.04	9.03	2.93
Tampa-St. Pete. (FL)	8.85	4.32	10.49	11.34	6.36
Tucson (AZ)	0.07	-1.39	5.82	5.80	0.78
Tulsa (OK)	0.84	0.34	-0.28	2.05	0.16
Norfolk (VA)	10.27	11.65	8.60	6.98	5.78
Visalia (CA)	7.26	-2.11	8.61	4.44	0.28
Washington (DC)	6.11	8.41	7.72	4.95	1.27
Wichita (KS)	1.26	0.79	1.68	5.88	0.33
Wilmington (NC)	-4.86	4.87	2.02	-3.06	-15.66
Winston (NC)	8.71	6.98	11.60	10.23	6.76
Worcester (MA)	8.90	10.71	8.84	4.00	9.05
Youngstown (OH)	7.30	1.50	-0.91	25.30	9.20

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

E Summaries of Input Data

This appendix provides background details for the data described in Section 3 and employed in the empirical test for tickets and slopes in Section 4 and the hedonic estimators in Section 6. The main purpose is to report which extracts of data were available for each application.

Tables E1, E2, and E3 detail the data used in the model presented in Section 4. Table E1 reports on the availability of property transactions data by market. Table E2 provides summary statistics on the neighborhood amenity data. Note that the table reports the data in the units in which the attributes are reported, but before entering the second stage model, the data is locally standardized to have mean zero and unit variance, in order to make it comparable across amenities and across markets. Table E3 provides a summary of the neighborhoods for which we have ticket and slope estimates outputted from the first stage and inputted to the second stage. The table shows which markets were contributing to each second stage model.

Table E4 provides summary statistics on the data in our school boundary regressions, including the number of boundaries and schools, the properties and transactions matched to boundaries, and the standard deviation of differences in test scores across boundaries. Some markets used in the Section 4 analysis were not available for boundary hedonic analysis, which can be traced back to their lack of sharp school boundaries as reported in Table E1.

Table E1: Summary of Data in First Stage Capitalization Function Regressions

City	Sub-Markets	Properties	Transactions	Mean Price ($ 1000)	Neighborhoods Total	AB	Distance
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)	3	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)	1	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	20	20	
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)	6	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	49	49	
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	2	2	
Charleston (WV)	1	1,556	1,727	137.9	12		12
Charleston (SC)	1	50,035	66,642	255.4	71	67	4
Charlotte (NC)	1	176,919	252,779	213.2	179	160	19
Chattanooga (TN)	1	7,303	9,972	104.5	47	1	46
Chicago (Cook) (IL)	3	193,148	251,164	244.1	948	390	558
Chicagoland (IL)	4	186,612	257,837	236.7	942	96	846

Continued on next page

Table E1: Summary of Data in First Stage Capitalization Function Regressions

City	Sub-Markets	Properties	Transactions	Mean Price ($ 1000)	Neighborhoods Total	AB	Distance
Chico (CA)	1	14,567	22,192	185.6	45	12	33
Cincinnati (OH)	1	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)	1	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	11	11	
Dallas (TX)	3	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	44	44	
Denver (CO)	2	202,310	284,325	259.9	444	320	124
Des Moines (IA)	1	39,929	66,422	150.1	130	40	90
Detroit (MI)	3	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
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	58	46	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	23	22	1
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

Continued on next page

Table E1: Summary of Data in First Stage Capitalization Function Regressions

City	Sub-Markets	Properties	Transactions	Mean Price ($ 1000)	Neighborhoods Total	AB	Distance
Hartford (CT)	1	71,800	85,859	239.7	199	141	58
Hickory (NC)	1	20,550	28,076	128.1	105		105
Houston (TX)	4	144,515	554,714	208.1	711	711	
Huntsville (AL)	1	28,673	37,380	188.2	61	25	36
Indianapolis (IN)	1	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	168	142	26
Kansas City (MO)	1	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	63	63	
Lancaster (PA)	1	32,905	40,277	176.2	111	1	110
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)	1	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	53	39	14
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)	2	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	35	26	9
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	30	30	
Memphis (TN)	1	75,674	114,345	152.8	167	143	24
Miami (FL)	3	392,135	578,009	231.6	649	249	400
Milwaukee (WI)	1	53,223	71,596	132.0	137	137	
Minneapolis (MN)	1	117,566	263,808	218.6	323	323	

Continued on next page

Table E1: Summary of Data in First Stage Capitalization Function Regressions

City	Sub-Markets	Properties	Transactions	Mean Price ($ 1000)	Neighborhoods Total	AB	Distance
Mobile (AL)	1	36,428	55,651	136.8	53	48	5
Myrtle Beach (SC)	1	20,454	28,456	202.5	21	21	
Naples (FL)	1	24,241	33,107	353.1	28	28	
Nashville (TN)	1	153,929	227,841	193.8	280	91	189
New Haven (CT)	1	44,091	53,553	246.2	209	11	198
New Orleans (LA)	1	347	388	134.0	4		4
New York City (NY)	2	126,520	148,607	520.5	538	38	500
New York City (NJ)	1	247,922	298,873	381.8	1256	126	1130
New London (CT)	1	15,249	18,160	239.3	82	2	80
Ocala (FL)	1	39,331	51,787	106.2	28	28	
Ogden (UT)	1	34,079	48,260	207.1	112	83	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)	1	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	52	52	
Panama City (FL)	1	15,182	19,560	154.6	18	18	
Pensacola (FL)	1	31,441	40,512	156.0	44	44	
Philadelphia (PA)	3	334,220	412,286	216.9	851	492	359
Phoenix (AZ)	2	337,627	590,264	184.3	572	388	184
Pittsburgh (PA)	1	101,225	118,314	133.2	326	58	268
Portland (ME)	1	4,932	5,303	258.0	32	6	26
Portland (OR)	1	122,128	166,791	261.5	354	307	47
Port St. Lucie (FL)	1	35,750	66,827	146.9	30	3	27
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	98	74	24
Racine (WI)	1	6,745	9,110	96.6	13	13	

Continued on next page

Table E1: Summary of Data in First Stage Capitalization Function Regressions

City	Sub-Markets	Properties	Transactions	Mean Price ($ 1000)	Neighborhoods Total	Neighborhoods AB	Neighborhoods Distance
Raleigh (NC)	1	109,787	144,351	212.5	138	123	15
Reno (NV)	1	40,734	64,492	225.3	65	62	3
Richmond (VA)	1	89,320	125,431	226.9	187	116	71
Riverside (CA)	2	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)	1	177,616	304,518	257.2	367	148	219
St. Louis (MO)	3	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)	1	100,339	139,581	178.1	375	173	202
San Diego (CA)	2	166,834	260,342	438.5	456	221	235
San Francisco (CA)	3	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)	3	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
Tampa-St. Pete. (FL)	1	215,850	301,422	167.2	246	246	
Toledo (OH)	1	36,516	51,996	96.3	154	15	139
Tucson (AZ)	1	69,553	106,660	237.6	130	128	2
Tulsa (OK)	1	63,521	83,011	143.3	170	73	97
Norfolk (VA)	1	91,452	126,901	229.6	210	198	12
Visalia (CA)	1	30,790	49,238	159.1	124	26	98
Washington (DC)	3	309,425	453,097	372.0	746	720	26

Continued on next page

Table E1: Summary of Data in First Stage Capitalization Function Regressions

City	Sub-Markets	Properties	Transactions	Mean Price ($ 1000)	Neighborhoods Total	Neighborhoods AB	Neighborhoods Distance
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		11,544,960	17,316,040		32,679	14,035	18,644

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

Table E2: 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
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

Continued on next page

Table E2: 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
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
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

Continued on next page

Table E2: 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
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
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

Continued on next page

Table E2: 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
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
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
Roanoke (VA)	87.0	9.8	7.3	6.0	0.00	0.00	0.00	0.00

Continued on next page

Table E2: 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
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
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 E3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Replace Cost	In: Property Attributes
Akron (OH)	84	0.32	0.80	2	34	0.19	yes	yes
Albany (NY)	119	0.22	0.80				yes	yes
Albuquerque (NM)	112	0.86	0.57	3	78	1.19	yes	
Allentown (PA)	96	0.29	0.79	2	11	0.81	yes	yes
Ann Arbor (MI)	24	1.30	0.72	1	18	3.42	yes	yes
Asheville (NC)	48	-0.48	0.67	1	12	0.76	yes	yes
Atlanta (GA)	591	0.18	0.58	15	105	0.60	yes	yes
Augusta (GA)	70	-1.24	0.63	2	7	-1.03	yes	yes
Austin (TX)	197	0.29	0.52	4	113	1.91	yes	
Bakersfield (CA)	124	0.58	0.69				yes	yes
Baltimore (MD)	356	1.77	0.72	3	93	-0.39	yes	
Baton Rouge (LA)	33	-0.97	0.63				yes	
Bend (OR)	20	1.07	0.39	1	10	0.82	yes	yes
Birmingham (AL)	95	-0.21	0.74				yes	yes
Boise City (ID)	95	-0.54	0.56	3	53	-0.74	yes	yes
Boston (MA)	570	2.19	0.82	15	117	0.74	yes	yes
Boulder (CO)	39	3.92	0.55	2	6	3.62	yes	yes
Bradenton (FL)	49	1.41	0.50	2	6	1.76	yes	yes
Bridgeport (CT)	130	0.39	0.83				yes	yes
Buffalo (NY)	128	-0.35	0.87	3	40	-1.17	yes	yes
Canton (OH)	62	-0.98	0.77				yes	yes
Cape Coral (FL)	2	-0.06	0.39				yes	yes
Charleston (WV)	7	-1.44	0.79				yes	yes
Charleston (SC)	60	-0.99	0.59	2	16	-0.70	yes	yes
Charlotte (NC)	170	-0.40	0.69	1	68	-0.97	yes	yes
Chattanooga (TN)	22	-1.03	0.66				yes	
Chicago (Cook) (IL)	690	-0.24	0.87				yes	yes
Chicagoland (IL)	602	0.52	0.68	18	111	-0.18	yes	yes
Chico (CA)	25	1.42	0.63					yes

Continued on next page

Table E3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Replace Cost	In: Property Attributes
Cincinnati (OH)	165	-0.53	0.75	6	40	-0.60	yes	yes
Cleveland (OH)	232	-0.05	0.82	15	121	-0.54	yes	yes
Colorado Springs (CO)	105	1.10	0.58	1	69	0.38	yes	yes
Columbia (SC)	88	-0.80	0.61	2	17	-0.53	yes	yes
Columbus (OH)	231	0.30	0.74	6	113	0.50	yes	yes
Corpus Christi (TX)	55	-0.40	0.70	1	39	-0.89	yes	
Corvallis (OR)	10	0.60	0.63	2	8	0.24		yes
Dallas (TX)	951	-0.31	0.60	31	592	-0.19	yes	yes
Dayton (OH)	87	-0.52	0.79	4	28	-1.50	yes	yes
Deltona (FL)	44	0.72	0.55	2	5	0.78	yes	yes
Denver (CO)	373	1.36	0.54	8	194	1.25	yes	yes
Des Moines (IA)	89	-1.04	0.74				yes	yes
Detroit (MI)	529	0.35	0.79	20	230	0.09	yes	yes
Dover (DE)	17	1.22	0.67				yes	yes
Duluth (MN)	21	-0.43	0.81				yes	yes
Durham (NC)	51	0.92	0.67	2	25	1.41	yes	yes
El Paso (TX)	114	1.00	0.65	1	97	0.57	yes	yes
Eugene (OR)	42	0.64	0.63				yes	yes
Fayetteville (NC)	51	-0.65	0.61	2	22	-1.15		yes
Fort Wayne (IN)	59	-1.03	0.77				yes	yes
Fresno (CA)	154	1.79	0.66	4	104	1.39	yes	yes
Gainesville (FL)	22	0.24	0.52	1	10	0.09		yes
Grand Junction (CO)	22	0.73	0.55				yes	yes
Grand Rapids (MI)	29	0.22	0.75				yes	yes
Greensboro (NC)	101	-0.44	0.71	4	51	-0.36	yes	yes
Greenville (SC)	61	-1.12	0.67	2	5	-0.97		yes
Harrisburg (PA)	60	0.88	0.76				yes	yes
Hartford (CT)	165	0.86	0.80				yes	yes
Hickory (NC)	58	-0.59	0.67	2	9	-0.48	yes	yes

Continued on next page

Table E3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Replace Cost	In: Property Attributes
Houston (TX)	706	-0.16	0.52				yes	yes
Huntsville (AL)	45	-1.62	0.74	2	31	-1.83	yes	
Indianapolis (IN)	216	-0.83	0.72				yes	yes
Jackson (MS)	8	-1.21	0.61				yes	
Jacksonville (FL)	148	0.18	0.63	1	97	1.08	yes	yes
Kansas City (MO)	320	-1.00	0.73	12	148	-0.76	yes	yes
Knoxville (TN)	75	-0.27	0.69	2	5	-0.90	yes	yes
Lakeland (FL)	63	0.46	0.57				yes	yes
Lancaster (PA)	69	0.61	0.77	5	21	0.07	yes	yes
Lansing (MI)	49	0.79	0.75				yes	yes
Las Vegas (NV)	182	-1.15	0.46				yes	yes
Lexington (KY)	36	0.54	0.68				yes	yes
Lincoln (NE)	41	-0.12	0.70	1	36	0.96	yes	yes
Little Rock (AR)	100	-1.06	0.63	3	27	-1.34	yes	
Los Angeles (LAC) (CA)	1,113	0.89	0.85				yes	yes
Los Angeles (OC) (CA)	370	0.70	0.61				yes	yes
Louisville (KY)	47	-0.81	0.67	1	7	-1.26	yes	yes
Madison (WI)	32	0.65	0.70				yes	yes
Manchester (NH)	47	2.50	0.72	1	12	0.11	yes	yes
McAllen (TX)	135	-0.47	0.56	6	50	-0.36	yes	yes
Medford (OR)	26	1.33	0.62	1	12	1.05	yes	yes
Memphis (TN)	137	1.75	0.65	2	7	1.40	yes	yes
Miami (FL)	235	1.02	0.48	14	65	0.94	yes	yes
Milwaukee (WI)	125	0.61	0.82	3	87	-0.90	yes	yes
Minneapolis (MN)	317	0.61	0.68	6	24	0.41	yes	yes
Mobile (AL)	46	-1.75	0.68	1	22	-2.34	yes	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	yes

Continued on next page

Table E3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Replace Cost	In: Property Attributes
New Haven (CT)	132	0.20	0.82				yes	yes
New York City (NY)	336	1.08	0.89	5	40	-0.21	yes	yes
New York City (NJ)	777	1.31	0.84	21	183	0.05	yes	
New London (CT)	39	0.66	0.78				yes	yes
Ogden (UT)	96	0.18	0.63	8	60	-0.27	yes	yes
Oklahoma City (OK)	193	-0.60	0.67	6	121	-0.78	yes	yes
Omaha (NE)	132	-0.78	0.73	1	76	0.04	yes	yes
Orlando (FL)	200	0.69	0.55	6	50	0.46	yes	yes
Ventura (CA)	123	1.83	0.60				yes	yes
Melbourne (FL)	52	0.86	0.65	4	26	0.59	yes	yes
Panama City (FL)	18		0.54				yes	yes
Pensacola (FL)	42	-1.05	0.63				yes	yes
Philadelphia (PA)	660	1.52	0.81	5	166	0.03	yes	yes
Phoenix (AZ)	516	1.11	0.49	13	371	1.31	yes	
Pittsburgh (PA)	186	0.23	0.87	6	46	0.46	yes	yes
Portland (ME)	14	1.83	0.63				yes	yes
Portland (OR)	310	0.61	0.63	14	137	0.27	yes	yes
Poughkeepsie (NY)	84	0.26	0.77				yes	yes
Providence (RI)	175	2.32	0.84	6	55	0.27	yes	yes
Provo-Orem (UT)	86	0.41	0.57	5	38	-0.44	yes	yes
Racine (WI)	13	-0.28	0.80	1	13	-1.44	yes	yes
Raleigh (NC)	131	0.76	0.62	3	46	1.18	yes	
Reno (NV)	61	-0.09	0.50	2	47	0.01	yes	yes
Richmond (VA)	151	-0.43	0.65	2	7	-0.42	yes	yes
Riverside (CA)	559	0.98	0.60	16	130	0.89	yes	yes
Roanoke (VA)	39	-0.64	0.69	1	17	-0.67	yes	yes
Rochester (NY)	93	-0.36	0.79				yes	yes
Sacramento (CA)	273	0.78	0.60				yes	yes
St. Louis (MO)	323	-0.83	0.76	14	91	-1.18	yes	yes

Continued on next page

Table E3: Summary of Data in Second Stage Ticket-and-Slope Regressions

City	Metro Nhoods	Metro WRI	Old Stock Share	Munis	Muni Nhoods	Muni WRI	In: Replace Cost	In: Property Attributes
Salem (OR)	56	0.64	0.59	1	26	0.86	yes	yes
Salt Lake City (UT)	138	-0.35	0.63	8	86	0.04	yes	yes
San Antonio (TX)	276	-0.17	0.66	3	190	2.69	yes	yes
San Diego (CA)	370	0.87	0.60				yes	yes
San Francisco (CA)	519	1.12	0.79	16	156	1.41	yes	yes
San Jose (CA)	225	0.40	0.68				yes	yes
Savannah (GA)	38	-0.27	0.72	1	17	0.12	yes	yes
Scranton (PA)	27	0.20	0.82	2	7	-0.02	yes	
Seattle (WA)	475	1.58	0.70	18	182	1.48	yes	yes
South Bend (IN)	39	-1.02	0.82				yes	yes
Springfield (MA)	92	0.97	0.83	7	59	-0.13		yes
Stockton (CA)	89	0.88	0.67				yes	yes
Syracuse (NY)	99	-0.68	0.79				yes	yes
Tampa-St. Pete. (FL)	245	-0.05	0.53	5	79	0.87	yes	yes
Toledo (OH)	97	-0.76	0.77	5	54	-1.69	yes	yes
Tucson (AZ)	121	1.91	0.53	4	86	0.40	yes	
Tulsa (OK)	119	-0.99	0.66	2	63	-1.24	yes	
Norfolk (VA)	196	0.20	0.66	6	151	-0.14	yes	yes
Visalia (CA)	78	0.76	0.65					yes
Washington (DC)	694	0.51	0.67	8	83	0.63	yes	yes
Wichita (KS)	106	-1.36	0.77	5	20	-1.25	yes	yes
Wilmington (NC)	38	-0.93	0.55	1	12	0.26	yes	yes
Winston (NC)	57	-0.69	0.70	2	30	-0.22	yes	yes
Worcester (MA)	98	3.13	0.82				yes	yes
Youngstown (OH)	50	-0.23	0.81	2	6	-0.25	yes	yes

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

Table E4: 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
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

Continued on next page

Table E4: Summary of Data in Hedonic School Boundary Regressions

City	Boundaries	Schools	Properties	Transactions	Score Diff SD
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
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

Continued on next page

Table E4: Summary of Data in Hedonic School Boundary Regressions

City	Boundaries	Schools	Properties	Transactions	Score Diff SD
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
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

Continued on next page

Table E4: Summary of Data in Hedonic School Boundary Regressions

City	Boundaries	Schools	Properties	Transactions	Score Diff SD
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
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.