Capitalization as a Two-Part Tariff: The Role of Zoning*

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February 2019

Abstract

This paper shows that the capitalization of local amenities is effectively priced into land via a two-part pricing formula: a "ticket" price paid regardless of the amount of housing service consumed and a "slope" price paid per unit of services. We first show theoretically how tickets arise as an extensive margin price when there are binding constraints on the number of households admitted to a neighborhood. We use a large national dataset of housing transactions, property characteristics, and neighborhood attributes to measure the extent to which local amenities are capitalized in ticket prices vis-á-vis slopes. We find that in most U.S. cities, the majority of neighborhood variation in pricing occurs via tickets, although the importance of tickets rises sharply in the stringency of land development regulations, as predicted by theory. We discuss implications of two-part pricing for efficiency and equity in neighborhood sorting equilibria and for empirical estimates of willingness to pay for non marketed amenities, which generally assume proportional pricing only.

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

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

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*We thank David Albouy, Jan Brueckner, Bill Fischel, and Edson Severnini for helpful discussions, and participants at the 2018 AREUEA-ASSA meetings, the 2018 World Conference of Environmental and Resource Economists, the 2017 NBER Summer Institute, the South Carolina Applied Microeconomics Day workshop, the 2016 Urban Economics Association meetings, and seminar participants at the University of Alabama, Clemson University, the Federal Reserve Board, the Federal Reserve Bank of Philadelphia, the University of Houston, Marquette University, the University of North Carolina-Charlotte, and the University of Notre Dame, the University of Richmond, PERC, the University of Southern California, and Syracuse University for useful comments. We gratefully acknowledge the Social Science Research Institute (SSRI) at Duke University, and Pat Bayer, Chris Timmins, and Eduardo Jardim, in particular, for assistance with accessing the real estate data. We thank Hal Martin, Cody Reinhardt, Jacob Siegel, Ben Harrell, Bret Hewett, Vicky Sparks, and Alexander Gordon for research assistance. We thank the Lincoln Institute of Land Policy for generous financial support of this research. Banzhaf is additionally grateful to PERC for a Lone Mountain fellowship to work on this project.

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1 Introduction

Tiebout (1956) famously argued that there is a market-like process for allocating local public goods, with local jurisdictions supplying them to attract residents and 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. Tiebout's simple model assumed that non-distortionary head taxes serve as the price. As with a well-functioning market for private goods, the head tax serves as a price on benefits, a price that optimally coordinates the distribution of amenities. Households then sort into communities based on their differing demands for those amenities. 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), 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 no longer a two-part tariff in household sorting processes but only the gross-of-tax price of housing. Accordingly, most economists working with Tiebout models have ignored the role of tickets at the extensive margin. This choice has empirical and theoretical implications. The workhorse models of housing demand, including hedonic price regressions and structural models of locational choice, invariably assume prices are proportionate in some bundle of housing services (see Taylor (2017) and Kuminoff et al. (2013) for respective reviews). If housing is priced according to a two-part tariff, these models are misspecified, with biased estimates of housing price and income elasticities and willingness to pay for amenities.

The implications for theory and welfare are equally serious. If locational sorting is rationed only by proportional housing prices, it would give rise to a potential "jurisdictional choice externality," in which poorer households try to buy the smallest house on the block in richer neighborhoods (Fischel (1985), Calabrese et al. (2011)). This dynamic is problematic if public goods are congested, so that serving an additional household either subtracts from the benefit received by others or requires additional funding. An example might be education, in which services are determined by per capita expenditures. Because too many people crowd into a community to get a share of the amenity or tax base, Tiebout's "market for public goods" is anything but efficient. In fact, in a simulation model of Tiebout sorting, Calabrese et al. (2011) find this problem is so severe that the congestion entirely negates any gain from Tiebout sorting processes, so households are better off with a single homogeneous community.

Hamilton extended Tiebout's model to account for just such issues in Hamilton (1975) and Hamilton (1976) (see Fischel (1985) and Fischel (2001) discussion). He suggested that zoning and other land-use restrictions can prevent such distortions by restricting access to a community. Hamilton developed his argument using some very special cases, which in our view has masked the potential generality of his results. In particular, Hamilton (1976) developed a model focused on the fiscal transfers of the property tax, making it seemingly irrelevant for non-financed amenities. Similarly, Hamilton (1975) developed a model with homogeneous communities and no capitalization of amenities into housing prices. However, empirical work routinely finds evidence of capitalization (Ross and Yinger (1999)), seemingly invalidating Hamilton's model.

In this paper, we offer a broader perspective on the manner in which local amenities may be capitalized. We first generalize Hamilton's intuition using a model that includes different kinds of land-use restrictions and exogenous amenities. This generalization allows us both to isolate the key driving factors generating the tickets in two-part pricing and to identify the implications for capitalization. We show that *any* local land use restriction that places a binding constraint on the *number* of housing units in a neighborhood introduces an extensive-margin price on housing units that mimics a head tax: each neighborhood will have its own "ticket" price for entry. In general, housing costs consist of a two-part tariff, an entry ticket plus a per-unit cost for additional housing services. We also show that amenities will be capitalized into housing prices but when zoning or other frictions restrict the number of housing units, then amenities may be capitalized into the tickets instead of housing services. In contrast, minimum lot sizes impose a two-part tariff only on *individual* constrained households (those forced to purchase the minimum when they would otherwise choose less). But they only impart an extensive margin pricing function on the *neighborhood* when the restriction is binding on all households, as is the case in Hamilton (1975) and Brueckner (1981), in which case it is the same as a constraint on the number of housing units.

Second, we empirically test our theory. Specifically, we generalize models of capitalization by allowing public goods and amenities to affect both the "ticket" prices and the unit prices of housing services. We propose to account for both through the following family of models:

$$p_{ln} \quad = \quad \alpha_n + \beta_n h(x_{in}) + \epsilon_{in}$$

where n indexes neighborhoods, i indexes housing units, and h is the quantity of housing services at unit i, a (possibly nonlinear) function of underlying attributes x_{in}. The terms α and β represent, respectively, the intercept/ticket prices and the slope shifters/housing service gradient prices. Note this is *not* equivalent to the standard hedonic model with neighborhood fixed effects, which log-transforms the dependent variable. Such models have only one price variable per neighborhood (not two), are linear in parameters, and impose proportionate pricing. This model has two pricing variables per neighborhood, is non-linear in parameters (because of the non-linear restrictions in the interaction of the βs and $h()$), and imposes proportionality only through the βs but not the αs.

Taking this model to a large and comprehensive dataset of property values and attributes, we first test for whether the αs are the same in all neighborhoods within a metro area. We easily reject this hypothesis, finding that tickets are an important part of the housing price function, both statistically and economically. However, we recognize that this test depends on our functional form assumption that prices are an affine transformation of $h()$. As Landvoigt et al. (2015) and Epple et al. (2019) have recently emphasized, it is impossible to non-parametrically identify a price function separately from a housing services function; however, under the assumption of constant housing services functions, one can compare them across time and space. Accordingly, our more general strategy is to compare patterns in αs and βs across neighborhoods and cities, based on local amenities and land-use restrictions.

To test for the more general pattern, we have compiled what we believe to be the most comprehensive hedonic dataset ever assembled, combining breadth, depth, and granularity. We have obtained virtually every housing transaction between 2005-2011 in over 100 urban areas across the United States (about 13 million in all), complete with housing characteristics (e.g., living area, land area, room partitions) and geocoding to the level of address and latitude/longitude coordinates. This allows us to measure the price per unit of housing services (flexibly defined) as well as the potential extensive margin pricing at a fine geographic ("neighborhood") scale. In particular, we have matched each house in the transactions dataset to its elementary school attendance zone and obtained school-quality data for each school. To our knowledge this is the first national-level study to use educational data at such a fine and precise spatial scale. Other amenities include air pollution, hazardous waste sites, crime, and measures of centrality. Finally, the Wharton residential land use regulatory index (Gyourko et al. (2008)) is matched to the data at the city level (both metro area and municipality).

We find, as usual, that prices are higher in neighborhoods with higher amenities.[1] Importantly, however, we find that the extensive margin component (the αs) comprises a substantial share of the variation between neighborhoods. That is, neighborhoods are stratified by a shifting of their price functions as much or more so than a tilting via the price per unit of housing service. Testing our model, we find that, across two areas with low land-use restric-

[1]The focus of our tests is variation in local amenities within metropolitan areas. Regional differences like climate or labor market opportunities are swept up in nonparametric controls.

tions, amenities are relatively more capitalized into per-unit prices, whereas across two areas with heavy land-use restrictions, they are relatively more capitalized into tickets. Moreover, we find this pattern is particularly strong for land-use restrictions that one would expect would be binding on the number of housing units in an area, as our model predicts.

Our findings have three broader implications for the literature. First, in local public finance, they provide a new interpretation of the long-running debate between the Tiebout-Hamilton "benefit view" of the property tax and the Mieszkowski-Zodrow "new view" that it is distortionary (e.g., Mieszkowski and Zodrow (1989), Fischel (1992), Ross and Yinger (1999), Fischel (2001), Nechyba (2001), and Zodrow (2001)). A large literature has debated the relative merits of these models and purported to empirically test one against another. As discussed by Nechyba (2001), many of these tests are unsatisfying. Some argue that "capitalization is everywhere," with exogenous amenities and exogenous shocks to tax levels priced into housing, and that such capitalization is consistent with the benefit view. Others have argued that, because Hamilton's (1975) model has a constant price everywhere, capitalization contradicts the benefit view. Unfortunately, the participants in this debate appear to be talking past one another. The question is not *whether* public good levels are capitalized, but *how*. In the absence of zoning, amenities will be capitalized into the per-unit price of land and/or housing, as the demand for housing increases. But in the presence of zoning, the increased demand to live in an area may be capitalized into the tickets. To our knowledge, virtually all of the papers that have been interpreted as disproving the benefit view do so only under maintained hypotheses that rule out such two-part pricing. This includes the model of Carroll and Yinger (1994), which restricts the price of land to be uniform per square foot. More recently, Hilber and Vermeulen (2015) and Lutz (2015) find that exogenous demand shifters (local earnings and decreases in property tax burdens, respectively) increase housing capital in more rural areas and increase housing prices in more urban areas, where housing supply presumably is less elastic. These results are broadly consistent with our model, but they do not account for the possibility of two-part tariffs. Our model would further predict effects on land prices in the more rural areas and at the extensive margin in the more urban areas.

A second implication of our work is that the very large literature on “hedonic” housing prices routinely employs models that are fundamentally misspecified. This includes basic hedonic models focused on recovering marginal values, as well as hedonic models employed to find housing prices for use in discrete-continuous sorting models. Studies of willingness to pay for local public goods and of how households sort across neighborhoods on the basis of such goods might be reconsidered in light of the importance of capitalization into the extensive margin (ticket prices), as well as the intensive margin (marginal cost).

Third, our model relates to a growing literature on the regulatory costs of zoning. In particular, the logic of our strategy parallels that of Glaeser and Gyourko (2003), who test for differences in land at the intensive margin (a larger lot) and the extensive margin (an additional lot), and the difference in those differences across tightly and loosely regulated land markets. However, they do not interpret their findings in light of the debates over the efficiency of residential sorting. Moreover, while they account for a single “ticket price” at the extensive margin of a lot, they allow amenities to be capitalized only through unit land prices; in contrast, the possibility of amenities being capitalized through ticket prices is essential to our analysis. Finally, they do not derive these two measures from a single data source, as we propose to do.

Our paper also relates to recent work by Turner et al. (2014) and Albouy and Ehrlich (2018). These papers estimate the effect of zoning on housing prices by decomposing it into two components, the regulatory cost of zoning and the spatial externality (such as the utility of additional green space). Turner et al.’s identification strategy focuses on jurisdictional borders, relying on the idea that the regulatory cost of zoning falls only within a given jurisdiction while the externality varies smoothly across jurisdictional boundaries. Their model ignores the possibility of a fiscal transfer from congested public goods, which can be internalized from zoning, creating a public benefit that also changes discretely at the border.

Albouy and Ehrlich take a more structural approach, estimating the production function for housing as implied by a spatial equilibrium model. This approach does not rely on jurisdictional boundaries but ignores the possibility of ticket prices. In contrast, our model allows for these effects but ignores the regulatory costs.

In the remainder of this paper, we provide, in Section 2, a theoretical model of zoning and non-linear prices, as well as simulations illustrating the model. Sections 3 discusses additional implications of the model. Sections 4 and 5 describe our data and empirical strategy, respectively. Section 6 presents our results. Section 7 concludes the paper.

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. (See also Brueckner (1981) for an extension and more rigorous proof of Hamilton's results.) 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 minimum size of lots (or houses) and restrictions constraining the total number of lots (or housing units).

We argue that it is restrictions on the total number of lots that induces 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. To emphasize that fiscal transfers are not necessary to generate tickets, we focus on exogenous amenities in our theoretical model and how they effect land prices under these three regimes of land use controls.

Although we speak of "land use controls" for expositional purposes, we emphasize that frictions can be quite varied and need not be limited to literal government policies on land development. For example, merely having an established neighborhood with durable capital in place and numerous small property owners may present a friction or transactions cost to reconfiguration, even if some reconfiguration is permissible by the *de jure* land use regime.

For simplicity, we abstract away from housing capital in the formal exposition of the model, focusing only on the market for land. Below, we discuss how the model might generalize to pricing of housing more generally. We also consider such pricing in our empirical work.

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 jurisdiction in the city has a fixed land area. To focus attention on the (realistic) case where land restrictions prevent an optimal configuration of lots, we take as given an initial situation where each jurisdiction 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 jurisdiction and lot l which maximizes their utility, given a (possibly non-linear) price function over lot size in the neighborhood, $p_{ln} = p_n(h_{ln})$. (Note because G_n is uniform within neighborhoods, we implicitly subsume its effect on prices into the neighborhood-specific price function.) The equilibrium price function ensures that each lot is occupied. Given the utility function, it must be continuous and increasing in h within a neighborhood, and at a fixed 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 a technically necessary assumption.

Now consider the possibility of assembling or subdividing lots, or portions of 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 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 (per square foot). Otherwise, if it were higher, developers could make profits by assembling land so the jurisdiction 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:

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

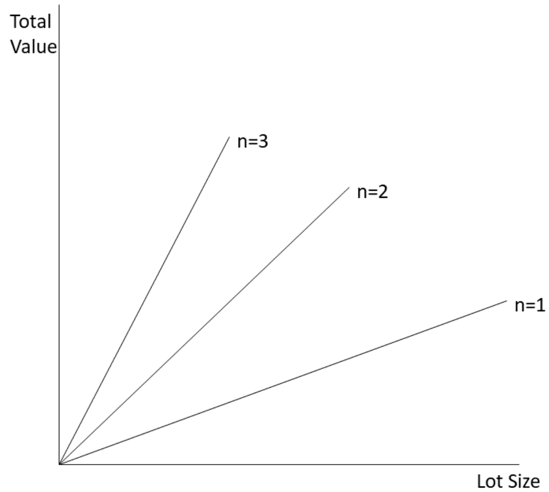
$$\frac{\partial p_n}{\partial h}|h_{ln} = \frac{p_{ln}}{h_{l,n}} \text{ for all } l, n \tag{1b}$$

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 (1a) gives

$$p_{ln} = \alpha_n + \beta_n h_{ln}, \tag{2}$$

Figure 1: Pricing Under Consensus View of Capitalization



for some constant of integration α_n. Dividing by square footage gives $p_{ln}/h_{ln} = \alpha_n/h_{ln} + \beta_n$. Equation (1b) then requires α_n=0 (except in the special case where h_{ln} is a constant h_n). 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, such that $(\beta_{n'} - \beta_n)(G_{n'} - G_n) > 0$ for $G_{n'} \neq G_n$. 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. Such a relationship is depicted in Figure 1. The figure shows the value of lots as an increasing function of lot size. Neighborhood 1 (n=1) is the community with lowest amenities. The slope of its price line depicts the price of land. Neighborhood 2 has nicer amenities and Neighborhood 3 nicer still: their price lines are steeper, indicating higher demand for land and hence higher prices per square foot.

2.2 Regulation as a Transaction Cost on Reconfiguring Lots

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 example, discussed by Hamilton (1976), is the case where low-income housing or other diversity rules force a particular mix of small and large housing units in the same neighborhood (and prevent arbitrage). More generally, one can imagine myriad rules and restrictions locking in an older housing stock and division of land, now out of equilibrium and preventing adjustment to current conditions (historical preservation, height restrictions, difficulty obtaining permits, holdup problems, etc.). By preventing existing lots from being subdivided or existing single family homes from being assembled into multi-dwelling units, such frictions restrict the number of housing units. Consequently, by making housing units scarce per se, they induce a two-part tariff, as we will show. To simplify the exposition, in the remainder of this section, we will speak of constraints on the number of lots, but the broader implication for housing units applies.

Consider again our case with exogenous G (and hence no fiscal transfers). If some neighborhood n has a relatively high value of G_n, so that there is a high demand for living there, it will have a high per-unit cost of land. Even so, there is nothing to 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.

Consider some neighborhood $n > 0$ with a binding constraint on the number of lots but no other land-use restrictions. Conditional on the number of lots, equilibrium condition (1a) 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 (2) also is satisfied, so $p_{ln} = \alpha_n + \beta_n h_{ln}$ for some constant of integration α_n. However, equilibrium condition (1b) is no longer satisfied. Instead,

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

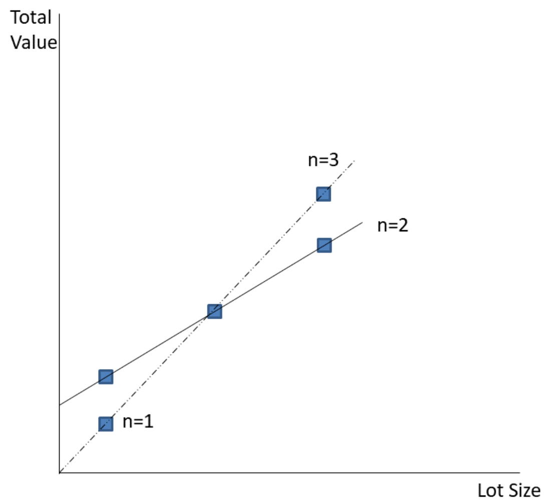
The marginal value of land at the intensive margin is lower than its value at the extensive margin, so developers would like to shrink the lots to create new ones if they could, but they are restricted from doing so.[2] As a consequence, the average value is shrinking in the lot size, which requires a constant term $\alpha_n > 0$ in the price function, or ticket. The ticket is the shadow value of the constraint on the number of lots.

Moreover, we normally would expect ticket prices to be increasing in G. As a starting point, 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. However, we cannot rule out a second-order effect through changes in the sorting equilibrium: 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, 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.

Hamilton (1976) provides one explanation for why such lock-in induces something like a head tax: fiscal transfers. Hamilton's logic is depicted in Figure 2. The horizontal axis shows the lot size, and the vertical axis shows the net-of-tax value of a lot. The point labeled n=1 represents a homogeneous community of all small lots; likewise the point n=3 represents

[2] Glaeser and Gyourko (2003) analyze this issue at the metro level.

Figure 2: Pricing Under Hamilton (1976)



a homogeneous community of all big lots. The dashed line connecting them illustrates a standard price function through the origin, as depicted in Figure 1. N=2 represents a neighborhood with mixed housing bundles, but in which the quantity of each type is fixed by zoning or other restrictions. Now, a small lot in n=2 has an advantage over an equal-sized lot in n=1 because it enjoys the tax base of the larger lots. Hence, it is more expensive. By the same token, the large lot in n=2 has a disadvantage relative to an equal-sized lot in n=3 because it must subsidize the public goods for residents who are pulling down the tax base. Hence, it is less expensive. The crucial consequence of all this is a *tilting* of price function for land within the second neighborhood: even if the marginal price of a square foot of land is constant within a community, as illustrated here by the straight lines connecting the points, the average cost (i.e., total cost divided by the lot size) is not constant. Prices must be computed with a neighborhood-specific intercept (i.e., tickets) as well as a per-unit cost of land.

Hamilton's paper and subsequent discussion have given the impression that fiscal transfers are necessary for this result. In fact, they are not. The transfers merely provide *one* reason why more people would like to crowd into the community and why (barring the constraint) arbitrage would lead to more dwelling units. But with the constraint on the number of dwelling units, they cannot, so there is a scarcity value on lots per se. It is this scarcity at the extensive margin – on the number of units – as well as on land at the intensive margin, which gives rise to the two-part tariff, with or without fiscal transfers.

2.3 Regulation as Minimum Lot Sizes

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, which is like the previous sub-section but with lots of homogenous size.

Although such lot size restrictions may *affect* density in equilibrium, 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 (1a) and (1b) are met. (If $\underline{h}$ is not binding at all lots, developers can re-allocate land to increase profits.) Thus, we still have $p_n(h_n) = \beta_n h_n$. Thus, there are no tickets in the community-level price function.

However, consider this scenario from the perspective of a constrained household. Conditional on living in neighborhood n, a household maximizes utility subject to the minimum lot size constraint. 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:

$$\max_{k,h_n} \quad u(k, G_n, h_n) + \lambda(y - k - \beta_n h_n) + \mu(h_n - \underline{h}) \tag{3}$$

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

$$\frac{\partial u}{\partial h} = \lambda \beta_n - \mu, \tag{4}$$

$$\mu(h_n - \underline{h}) = 0, \quad \mu \geq 0, \quad (h_n - \underline{h}) \geq 0. \tag{5}$$

For those households for whom the constraint does *not* bind, we have in Condition (5) $\mu = 0, (\underline{h} - h_n) > 0$. 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 (5) $\mu > 0, (\underline{h} - h_n) = 0$. For these households, it is useful to re-write the above constrained optimization problem using the following shadow pricing scheme (Neary and Roberts (1980)):

$$\max_{k,h_n} \quad u(k, G_n, h_n) + \widetilde{\lambda}(y + (\widetilde{\beta_n} - \beta_n)\underline{h} - k - \widetilde{\beta_n} h_n). \tag{6}$$

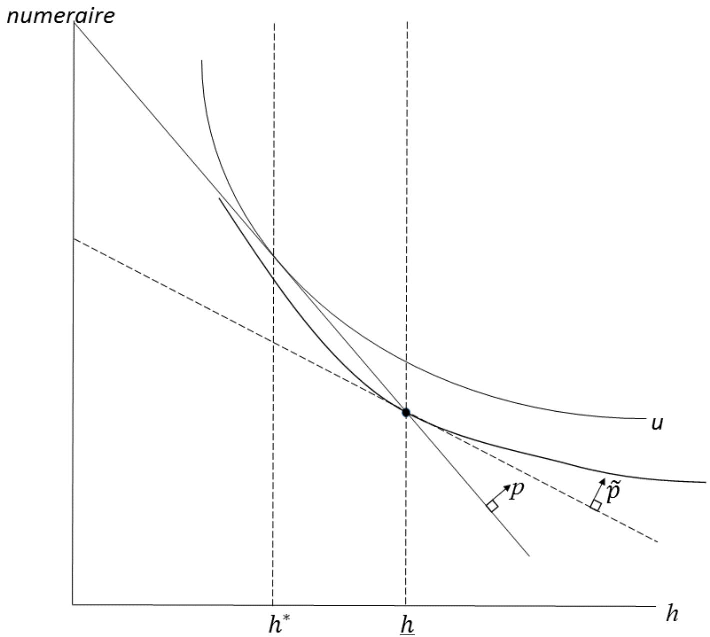
The first-order condition related to the household's choice of h is:

$$\frac{\partial u}{\partial h} = \widetilde{\lambda}\widetilde{\beta_n}. \tag{7}$$

That is, the problem in Expression (3) 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.[3] To see the equivalency of the problem when the constraint binds, note the first-order conditions (4) and (7) are the same if we just let $\widetilde{\lambda} = \lambda$ and $\widetilde{\beta_n} = \beta - \mu/\lambda$. In words, the marginal utility of income 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 3 compares the primal and dual problems. Given prices

[3] 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 3: Optimization with Constraint and with Shadow Values



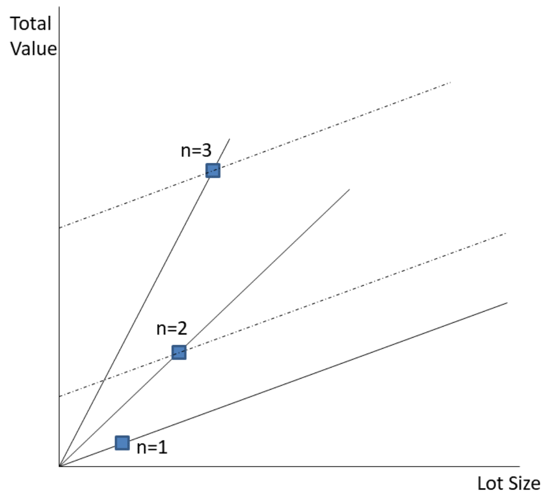
p, an unconstrained household would choose h^* and achieve utility level u. The constraint requires the household to consume at least $\underline{h}$, creating a wedge between the slopes of p and the indifference curve, of course lowering utility. However, there is a lower price $\widetilde{p}$ supporting 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 shows why a minimum purchase requirement is 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 (6), but they also can be modeled as being subject to a standard price, as in Expression (3). Both are valid, because either price function is consistent with a single data point. Figure 4 illustrates this situation, with three communities each with homogeneous lot sizes. The solid lines, the same as those in Figure 1, 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).

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 et al. (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.

Figure 4: Pricing Under Hamilton (1975)



2.4 Simulations

We illustrate these predictions with three policy simulations. For the three policy scenarios, we simulate an equilibrium using a neighborhood pricing function of the form $p_n = \alpha_n + \beta_n L$. Crucially, we examine when a ticket (nonzero α_n) is necessary to clear the market assigning households to lots within neighborhoods.

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 functions

$$u_i = (1 - \theta_i)\ln(z) + \theta_i \ln(h) + \phi_i G. \quad (8)$$

Substituting the budget constraint and price function for z yields the indirect utility functions

$$v_i = \max_{n,h_n} (1 - \theta_i)\ln(y_i - \alpha_n - \beta_n h_n) + \theta_i \ln(h_n) + \phi_i G_n. \quad (9)$$

In our simulations, we allow heterogeneity in income and tastes, with $y_i \sim$ u(40000, 100,000), $\theta_i \sim$ u(0.2, 0.4), and $\phi_i \sim$ u(0.1, 0.9).

Table 1: Summary Statistics from Simulations

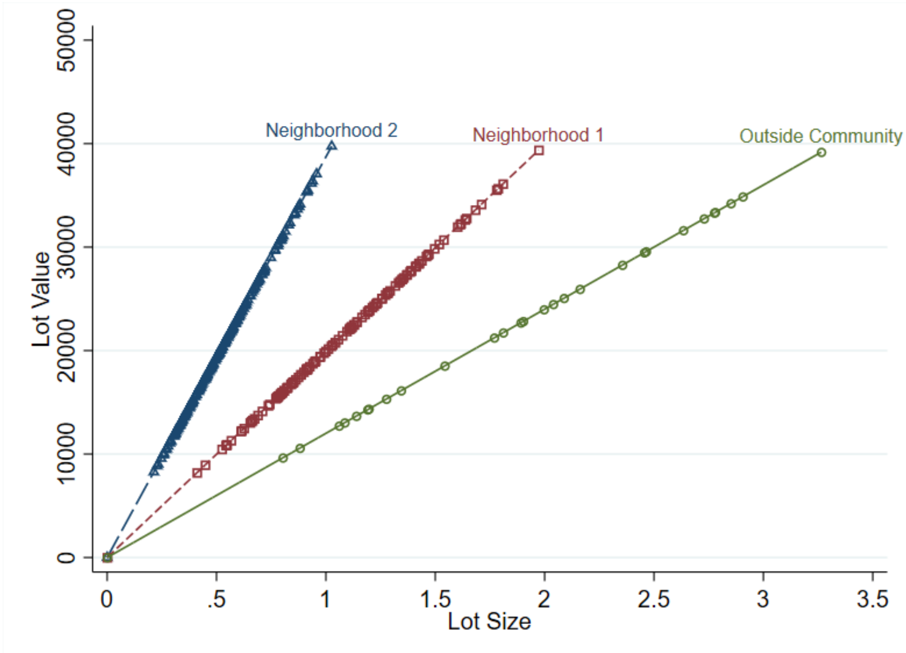
Attribute	Neighborhood	Scenario 1	Scenario 2	Scenario 3
Housing Units	1	3,075	4,037	4,036
	2	6,323	4,416	4,036
Avg Lot Size	1	1.08	0.83	0.83
	2	0.53	0.75	0.82
Price of Land	1	19,956	25,045	19,990
	2	38,713	43,889	21,419
Price of Ticket	1	0	0	6,439
	2	0	0	20,156
Mean Income	1	69,719	60,778	62,432
	2	70,213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

In the first scenario, there are no land use controls. 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 scenario, 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 5-7 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 5 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

Figure 5: Simulation 1: No Land-Use Controls

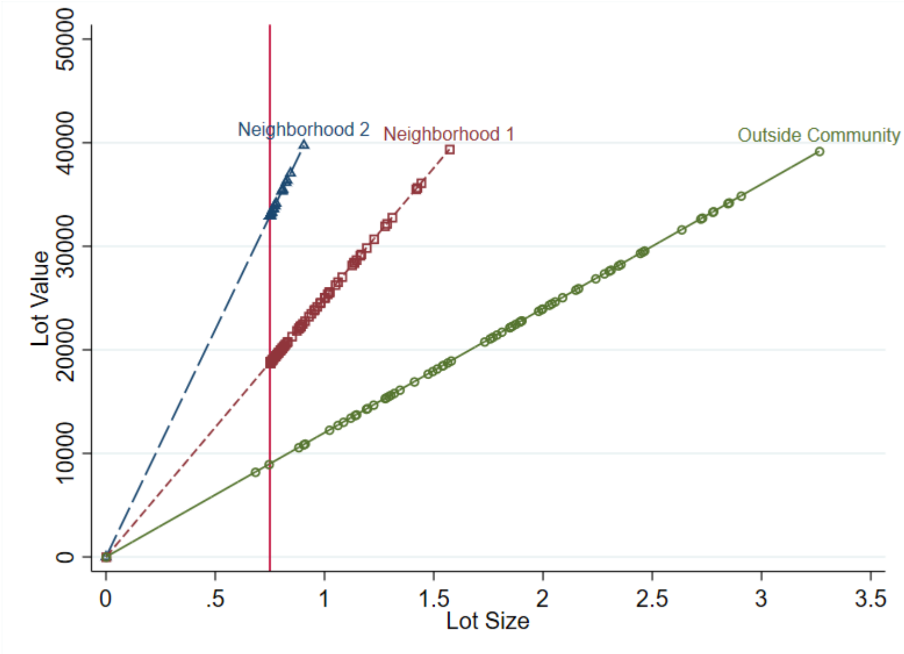


NOTES: The figure plots housing values to lot size for the simulated equilibrium under no land-use restrictions. Each point represents a housing unit, and lines are drawn for each community, extending through the vertical axis for visual reference.

both neighborhoods. Moreover, the heterogeneity in lot sizes decreases, as can be seen in Figure 6 (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 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.)

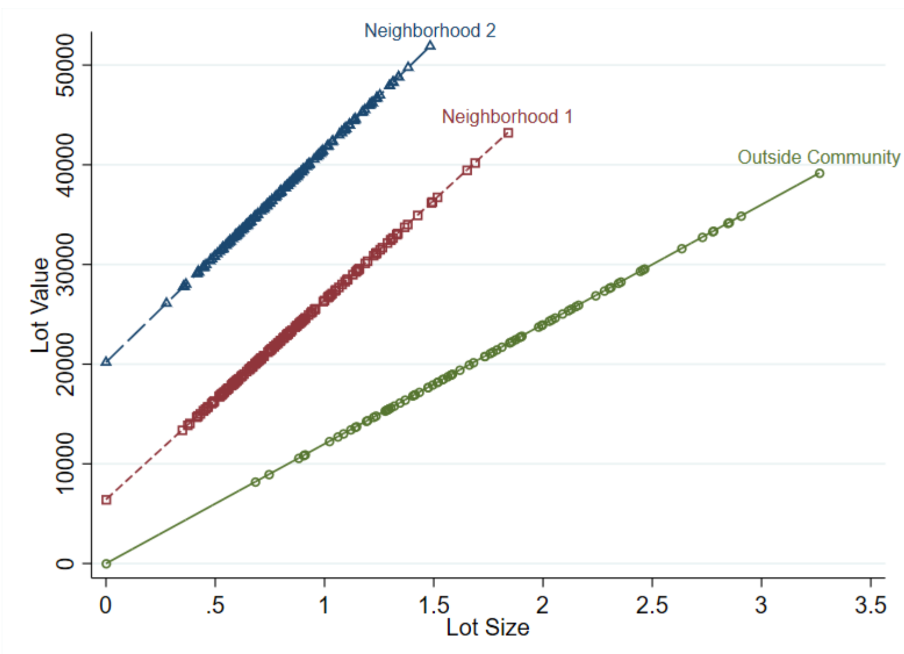
Finally, in Scenario 3, we see the introduction of entry tickets, as the extensive margin price is now necessary to satisfy the the condition on the number of lots in additional to equimarginality. At these parameters, we also see land prices falling and the difference between prices in the two neighborhoods collapsing, but in general, this will depend on preferences and incomes of the households in the economy.

Figure 6: 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.

Figure 7: 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.

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.

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:

$$h = (L^\rho + K^\rho)^{1/\rho}. \tag{10}$$

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

$$c(h) = \alpha_n + h \cdot (p_{L,n}^{\rho/(\rho-1)} + p_K^{\rho/(\rho-1)})^{(\rho-1)/\rho}, \tag{11}$$

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.

Taking the case of no land-use controls as in Section 2.1, $\alpha_n = 0$, so housing services are simply priced by β_n. Moreover, as discussed above, an increase in G will increase land prices, so capitalization will continue to take the form of Figure 1 when there are no land-use restrictions. Just as land becomes more expensive per-unit, so too do housing services. On the other hand, in the presence of restrictions on the maximum allowable number of lots, we would continue to expect G to be capitalized into α.

In practice, of course, we do not observe "housing services" per se, but rather a set of indicators like living area, lot size, bedrooms, 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 x.

We also acknowledge the possibility that the production function for housing could be more complicated that this CES example, giving rise to non-linearities in h. Also, in the presence of land-use restrictions, land cannot be optimally allocated as it would in the unrestricted cost minimization problem, so the price of housing even in this simple model would be convex in housing services, conditional on a given lot. Finally, if there are fixed costs in housing production, there might be a cost at the extensive margin for a housing unit. A fixed cost is *not* what we have termed a ticket price, however. A fixed cost results from the housing production technology and need not be systematically related to neighborhood amenities, whereas a ticket is a capitalization effect that arises in the locational equilibrium when the (unconstrained) quantity of houses demanded exceeds the constraint.

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 recently emphasized by Epple, Quintero, and Sieg (2018) and Landvoigt et al. (2015). Notably, we do not literally observe the limit of housing prices as lot sizes or dwelling areas shrink to zero. 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 by land-use restrictions.

3 Implications for Empirical Models of Housing and Location Choice

If land-use restrictions induce tickets, it would have important implications for empirical estimation of a wide range of economic models of housing and locational choice. Before moving onto an empirical test of our model, in this section, we discuss some of the modeling implications of capitalization via two-part pricing.

3.1 The Standard Hedonic Price Regression is Mis-specified

Hedonic price regressions are the most common approach to modeling housing markets, and by far the most common approach to hedonic regressions is to estimate a model with logged prices as the dependent variable and with neighborhood fixed effects:

$$ln(p_{in}) = \hat{\beta}_n + \hat{h}(x_i), \tag{12}$$

where p_{in} is the value of house i in neighborhood n and x_i is a vector of hedonic variables for house i (lot size, square footage, bathrooms, etc). That is, one regresses logged prices on neighborhood dummy variables to capture the local "price level" $\hat{\beta}_n$ and an estimated hedonic quantity index $\hat{h}(x_i)$.[4] See e.g., Sieg et al. (2002) for discussion. This model is of course equivalent to

$$p_{in} = exp(\hat{\beta}_n)exp(\hat{h}(x_i)) = \tilde{\beta}_n\tilde{h}(x_i). \tag{13}$$

where $\tilde{\beta} = exp(\hat{\beta})$. That is, it is equivalent to a model with a price proportionate to a housing services function.

[4] Yinger (2015) offers a more general approach to estimating the functional form of the pricing function that results from a sorting equilibrium but still relies on proportional pricing (e.g., $P = p \cdot h$) without a ticket effect.

Suppose, however, that the true data-generating process is

$$p_{in} = \alpha_n + \beta_n h(x_i).$$

Compared with the true data-generating process, the standard model has only half the estimated neighborhood coefficients (N vs. $2N$). What might initially appear to be a ticket in Equation (12) is revealed in Equation (13) to be a log-transformed slope. Of course, where $\hat{h} = 0$, $exp(\hat{h}) = 1$ and the price function does have an intercept. The crucial point, however, is that $\hat{\beta}_n$ shifts the price function *proportionately*, transforming the slope as well as the intercept. With only N coefficients, it cannot separately identify ticket and slope effects.

To explore this issue, we conduct a simple numerical example using a two-neighborhood economy, where one neighborhood has a high g and one a low g. The first is more expensive, through α_n or through β_n, or both to varying degrees. To ground the example in empirical relevance, we calibrate the neighborhood price differences and derive a scalar-valued index of housing services using the national real estate data described in detail in Section 4.[5] We set the high-g neighborhood to be 72 percent more expensive at the median-sized property, and consider five scenarios in which the price difference between neighborhoods at the median housing service is 0, 25, 50, 75, and 100 percent because of the difference in ticket prices. In the first case, $\alpha_1 = \alpha_2$, and in the last $\beta_1 = \beta_2$.

Having generated property values in the two neighborhoods, we then estimate a (naive) log pricing model $ln(p_{in}) = \hat{\beta}_n + \hat{\phi} ln(h_i)$, analyzing its residuals and its counterfactual predictions for the consumption of housing services. Table 2 reports a summary of these results. First, panel A shows the residuals of $p_{in} - exp(ln(\hat{p_{in}}))$. The first row shows the mean value of the residual by neighborhood, and the subsequent rows show the mean residual for three bins of

[5]For the between-neighborhood price differences, we take the ratio of the 75^{th} percentile neighborhood to the 25^{th} percentile across metro areas and then take the median of this ratio arose metro areas in our data, which we find to be 1.72. For housing services, we take the national distribution of lot size and living area, trimming the upper and lower one percent tails and forming a grid of property sizes in between. We then set $h = 33.51 + 0.35 \cdot lot\_area + 129.65 \cdot living\_area$, where the coefficients derive from a regression of prices on these two attributes.

house sizes (the first quartile, the middle two quartiles, and the fourth quartile). The first point to notice is the pattern in the residuals generated by the proportional pricing model. As mentioned earlier, it is not that the model forces the two neighborhoods to have the same intercept but that it forces the intercept to be related to the slope. Of course, least-squares regression correctly predicts the average (log) price but does so by tilting the price functions: the low-g neighborhood down and the high-g neighborhood up. This is because the regression assumes all properties in the high-g neighborhood are more expensive by a common factor. Thus, while the mean residual is zero (sometimes not exactly because of the log transformation), it varies systematically by g and h. In the low-g community, the residuals are systematically negative for small properties and positive for large properties. In the high-g community, the opposite is the case, with the residuals being positive for small properties and negative for large ones. Looking across columns of the table, we see that the larger is the importance of the ticket to the between-neighborhood price gaps, the larger are the magnitudes of the residual error. For example, when tickets comprise the full share of capitalization in the last set columns, the model overpredicts small properties by 4.26 percent in the low g neighborhood and overpredicts by 4.76 percent in the high g neighborhood. Conversely, it overpredicts large properties by 3.45 and underpredicts by 3.35 percent in the low and high neighborhoods, respectively.

This tilting can be seen graphically in Figure 8, which illustrates the 100 percent ticket case. These patterns motivate a simple, reduced form testable implication for the presence of tickets: if neighborhood prices vary because of tickets, we will find the pattern in the residuals of the log pricing model as exhibited in Figure 8.

3.2 Implications for Empirical Modeling

3.2.1 Consequences of Mis-specification of the Pricing Function

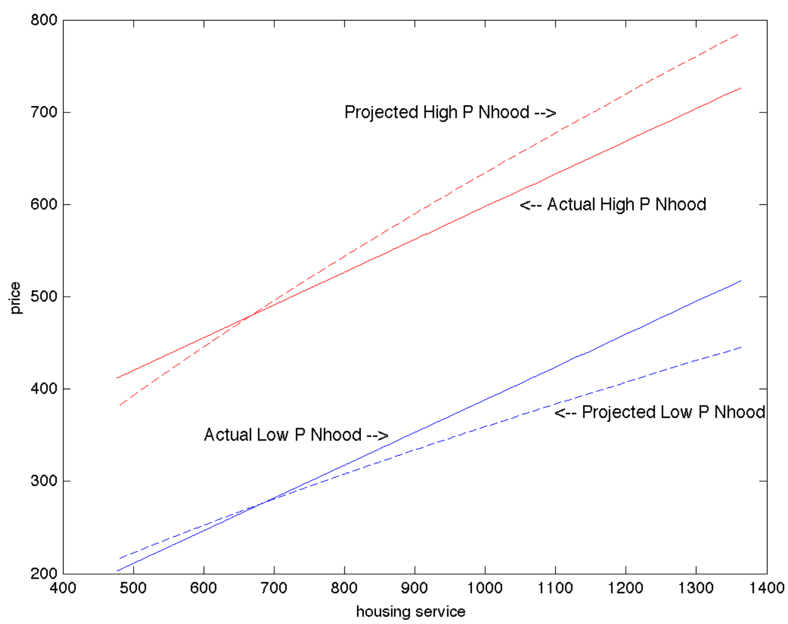
One common application of hedonic models is to estimate the marginal willingness to pay for amenities. Following Rosen (1974), households set their marginal willingness to pay for

Table 2: Simulation: The Log Price Model in the Presence of Tickets

Ticket Share	0		0.25		0.5		0.75		1	
Neighborhood g:	Low	High	Low	High	Low	High	Low	High	Low	High
Residuals (%)										
Mean	0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.03	0.05	0.05
Mean, Size p0-p25	-0.80	0.47	0.47	-0.96	1.73	-2.30	3.00	-3.56	4.26	-4.76
Mean, Size p25-p50	0.21	0.03	0.08	0.27	-0.05	0.48	-0.18	0.66	-0.30	0.81
Mean, Size p75-p100	0.39	-0.52	-0.61	0.42	-1.58	1.38	-2.53	2.35	-3.45	3.35
Counterfactual Prediction Errors (%)										
Mean	-0.01	0.05	4.13	7.28	10.08	15.98	18.80	26.59	32.07	39.74
Mean, Size p0-p25	0.47	-0.88	7.23	3.99	16.76	10.99	30.56	20.81	51.32	34.39
Mean, Size p25-p50	-0.14	-0.01	3.58	7.47	8.95	16.36	16.86	27.05	28.97	40.13
Mean, Size p75-p100	-0.25	1.11	2.15	10.16	5.66	20.18	10.92	31.43	19.06	44.30

NOTES: The table reports results from estimation of a log price model on simulated data for two neighborhoods distinguished by their amenity value (low or high). The sets of columns refer to simulations in which the extent of capitalization occurring through the ticket varies from 0 to 100 percent.

Figure 8: The Log Price Model in the Presence of Tickets



an amenity equal to the derivative of the price function with respect to that amenity. Of course, if the price function is misspecified, so too will be estimates of marginal willingness to pay. The preceding simulation, as exhibited in Figure 8, implies that the standard model is biased in a particular way. Because it ignores capitalization at the ticket but exaggerates capitalization into housing services, it will underestimate the marginal willingness to pay at small properties and overestimate it at large ones. This pattern may be particularly important when considering the *distributional* welfare effects of educational, environmental, and urban policies.

Another common application of locational choice models is in discrete-continuous models of household sorting (see e.g., Bayer et al. (2009), Kuminoff (2012), and Sieg et al. (2004) for examples, and Kuminoff et al. (2013) for a review).[6] In practice, these models first estimate a log-price hedonic model, then treat those prices as a neighborhood characteristic, along with amenities, that drives the discrete choice of location. This price function then afflicts the models with the same misspecification issues just discussed.

Often, estimated models are used to make predictions of locational equilibria in counterfactual situations. The flip side of distorting a price index is to distort the quantity index associated with an given level of expenditure. And without explicitly recovering tickets, the effective income adjustment is not made. The counterfactual predictions of these models for housing demand and where it is consumed (e.g., in which neighborhood) will be distorted accordingly. With the housing services/neighborhood quality misspecification pattern shown in Figure 8, analyzing distributional effects may be especially problematic.

We illustrate the potential pitfalls by using the estimated models of Table 2 to make counterfactual predictions of housing services demand. In panel B of Table 2, we use the log pricing model to project how much h a household spending p in the high-g neighborhood would consume if switching to the low-g neighborhood and vice versa. For simplicity, we assume Cobb Douglas utility so that the household is assumed to have constant expenditures

[6]A notable exception is the method of Bayer et al. (2007). This approach derives a choice probability of each individual property, which can in principle be decomposed into its respective two-part pricing.

across neighborhoods. (This is not essential to our point but is convenient because it yields arithmetic expressions for housing demand without simulating an actual model with particular utility parameters.) A household spending p_j would consume $h_k = \frac{p_j - \alpha_k}{\beta_k}$ if moving to neighborhood k.

The projected consumption in the log pricing model, however, is $\hat{h}_k = exp(\frac{ln(p_j) - (\hat{\beta}_k)}{\hat{\phi}})$. The proportional pricing model confuses the intercept and slope into one coefficient, under projecting the value of housing services in both neighborhoods (i.e., making $\hat{\phi}$ too low), and compensates by spreading the neighborhood coefficients apart, meaning it overpredicts the counterfactual amount of housing services consumed for *both neighborhoods*. In other words, the projection believes housing per unit is cheap in the low-g neighborhood, and so it overpredicts consumption for households relocating there, but while the projection treats services in the high-g neighborhood as expensive, it ignores the expenditure on the ticket. Visually, in Figure 8 this is the effect of the log price projection lines spreading apart faster than do the true price lines. The magnitude depends on the initial property size in an inverse way between the two neighborhoods. The projection bias is larger for small properties in the low-g neighborhood–in the 100 percent ticket case, for example, going from 51 percent for small properties to 19 for large–but the bias rises from 34 percent for small properties to 44 for large in the high-g neighborhood.

These results are for simulations in which the distribution of housing services h is the same in both neighborhoods. As alternatives, we repeat the exercise for situations in which the low-g neighborhood are smaller on average and one in which they are larger on average.[7] The patterns are similar in both cases to the base simulation, and are available upon request.

[7] Theory is ambiguous as to whether a high-G neighborhood would have larger or smaller properties. Roughly speaking, if income sorting dominates (and housing is a normal good), the housing in the high-G neighborhood will be larger, but if the price effect dominates, it will be smaller, as residents of better neighborhoods economize on home size. Our data exhibit each, with the ratio of median property sizes between the more and less expensive neighborhoods running the gamut from 0.05 to 20.

3.2.2 Tickets and the Price and Income Elasticities of Housing

As accounting for tickets would imply different prices and effective incomes, it would be expected to affect estimated price and income elasticities of housing demand. Insofar as price elasticities are identified off of between-neighborhood variation in prices, it is likely that the elasticities are underestimated when tickets are ignored. If high-g neighborhoods have larger houses (or higher-quality houses) than low-g neighborhoods, and if the between-neighborhood price differences are overestimated by the standard hedonic model–i.e., "too much slope," as shown in Figure 8–then when taking $\%\Delta h/\%\Delta\beta$, the denominator in the elasticity formula is "too big" using the standard approach. The same is true if price elasticities are identified off of within-neighborhood variation in the high-g neighborhoods (but the opposite in low-g neighborhoods). This pattern may help explain the low price elasticities estimated by, e.g., Sieg et al. (2004).

By the same token, when calculating the income elasticity of housing demand by taking $\%\Delta h/\%\Delta y$, the denominator would be too small if tickets are ignored, so estimated income elasticities will likely be overestimated. Because they reduce everybody's income by the same amount, tickets increase the percentage difference between the rich and poor within a neighborhood. On the other hand, the presence of tickets would add to to importance of accounting for unobserved tastes, especially in vertically differentiated models. Since Epple and Platt (1998), the literature has noted that there is too much income variation within neighborhoods and too little between neighborhoods to explain sorting patterns by income alone, so differences in tastes are required to fit the data. Higher tickets and lower per-unit prices in the high-G neighborhoods would amplify that point, since they imply that the poor cannot escape the high costs of the high-G neighborhoods by purchasing a small house. In other words, the two-part pricing model suggests that poor are paying even more for their housing bundle, so even stronger differences in tastes would be required to explain their sorting into the high-G neighborhoods. In contrast, in the low-G neighborhoods, larger houses are more expensive than predicted by the standard model (Figure 8), so again, even stronger differences in tastes would be required to explain the rich sorting into them.

4 Data

We next seek to measure the presence and extent of ticket-style capitalization and test whether it varies with land use frictions in the way the model predicts. The starting point for our data is a large national database of transactions. We divide these transactions by metropolitan area ("city") and sub-divide cities into neighborhoods, then link these housing data to a rich set of national public goods at the neighborhood level. In this section, we describe the data in more detail.

4.1 Housing Data

The housing data come from the real estate analytics firm CoreLogic.[8] The data merge two assemblages of public information: (1) records of transactions on the property deed (such as a sale or lien), including transaction dates, parties, values, and loan information; and (2) county tax assessor information, which includes information on property characteristics such as lot size, living area, year of construction, bedrooms, bathrooms, etc.[9] The data also include latitude and longitude coordinates of the property, which we use to match the properties to their neighborhood.

We have data on nearly 13.2 million transactions from 2005-2011 at 105 large US metro areas.[10] We clean the data of non-arms-length transactions and those with nominal prices, properties that transact multiple times on the same day, and transactions involving par-

[8] The data were made available to us via the Social Science Research Institute (SSRI) at Duke University. We are particularly indebted to Pat Bayer and Chris Timmins, as well as Eduardo Jardim, Gary Thompson, and Joshua Smith for technical assistance in accessing the data.

[9] These data were subject to the legacy collection method of overwriting tax assessor data each year, so this information is observed only for the final year of data – either 2011 or 2012, depending on the county – and would be obsolete if a property underwent a major renovation such as an addition of bedrooms.

[10] Dataquick, predecessor collector of the CoreLogic data, began collecting the deeds and assessor records prior to 2005 for most cities, but our public school information datas to 2009-2010, so we restrict our sample around those years. Note that the timeframe spans both "hot" and "cold" market periods in most metro areas.

tial property sales, subdivisions of parcels, and sales of vacant land. These cuts leave us with market rate transactions of occupiable properties. We are additionally interested in the property characteristics, so we further clean the data of properties with missing or obvious misreporting (e.g., land parcels and or living areas less than 500 square feet.) in the assessor file. We also drop two neighborhoods as having lot and dwelling area sizes that are outliers relative to their cities. These steps lead to a final estimation sample of 10,329,393 transactions. Table A1 reports summary statistics by metro area for the housing price and attribute variables.

As an initial check of the feasibility of the first stage model, we verify that there is sufficient heterogeneity in housing stock attributes within neighborhoods to estimate a land or housing services price. In the extreme case (e.g., Hamilton 1975), properties are stratified completely by neighborhood and perfectly homogeneous within. We find this is far from the case in the actual data. In Appendix Table A2, we decompose the variance of housing stock attributes like lot size and living area within and between neighborhoods. For this test, we use the full set of properties (not only those that transact in our sample window) and place these properties into municipalities to decompose variance. On average, four-fifths of the within-city variance in lot size or living area occurs within neighborhood. Property vintage is similarly distributed broadly within neighborhoods as well as between.

Finally, we obtained construction cost estimates from business information firm RS Means.[11] These data provide typical estimates of residential construction costs per square foot of living area, by size and quality of house, for each year and for most metro areas in our transactions record. We will use these as one method of decomposing physical capital from land values, as described in more detail below.

[11]RS Means provided, for a fee charged to Georgia State University, a subset of data electronically, and as well as access to their physical library of historical estimates books. We digitized these records by hand; we thank Bob Mewis of RS Means for help in coordination and Bret Hewett and Vicky Sparks for research assistance.

4.2 Amenities and Public Goods

Because our focus is on neighborhood-level pricing, we gather data on important amenities that vary across neighborhoods within metropolitan areas: education, distance to the city center, crime, and environmental quality. In contrast, attributes such as climate or labor market opportunities generally vary more between cities than within cities and will be absorbed in our model with city dummies. We match each property to its US census block using the latitude and longitude coordinates in the housing data and shapefiles from the U.S. Census Bureau. We then assign to blocks values of the amenities and then finally aggregate blocks back up to neighborhoods in the final analysis.[12]

Among the attributes we consider, public school quality is the one that changes most sharply at discrete boundaries. Accordingly, we define neighborhoods by elementary school attendance boundaries. The are 20,353 such neighborhoods represented in our final transactions dataset. We map the blocks to neighborhood boundaries via two methods. First, we have collected a national set of school zone maps, with 4th grade school attendance boundaries for use in GIS software, through the School Attendance Boundary Information System (SABINS) (SABINS (2011)).[13] The SABINS maps are not a complete partitioning of the U.S., but we were able to place 60.3% of Census blocks, comprising 69% of our housing transactions, into their 2010 school attendance boundary. For the remaining unmatched observations, we first assigned the blocks to their school district boundaries and then to the nearest school within the district, as in Downes and Zabel (2002).[14] Finally, using crosswalks provided by SABINS to the Common Core data, for each school we also have measures of 4th grade school quality, including math test scores and reading test scores. We use the percent of students in each school who pass their state's performance test, and convert these

[12]We match attributes to blocks rather than the properties themselves so that the amenity dataset is not specifically tied to the (proprietary) housing transactions dataset. Thus, we are able to share the amenity dataset with other interested researchers.

[13]These data and additional documentation are available at https://www.sabinsdata.org/.

[14]Recent work by Reinhardt (2016) analyzing this method in areas with precise boundary information suggests such a procedure works well and creates little measurement error.

percentages to z-scores by state.[15]

To measure neighborhood centrality within the metro area, we take the straight line surface distance (i.e., great circle distance), in miles, of the block latitude/longitude to the tallest structure in the metro area as a proxy for the city center. If there is more than one principal city in the metro area (e.g., San Francisco and Oakland, California), we use distance to the closest.

We also obtained measures of environmental quality available from the U.S. Environmental Protection Agency (EPA). First, as a measure of air pollution, we obtained the number of high-ozone days (exceeding the National Ambient Air Quality Standards) for each monitor in the US in 2009 from the US EPA. Distances from each monitor to each of over 11 million US Census blocks were computed, and each Census block was given an inverse-weighted average of the three nearest monitors. We then aggregated up these block-level data to our neighborhoods. Second, as a measure of undesirable land use, we obtained the number of sites listed under the Comprehensive, Environmental, Response, Cleanup, and Liability Act (CERCLA, commonly known as Superfund) within 3 kilometers of each block centroid to account for point-source environmental disamenities. Again, we averaged these blocks up to neighborhoods.

Finally, we obtain crime statistics from the Federal Bureau of Investigation's Uniform Crime Reports database from each local jurisdiction in the US, taking the sum of property and violent crime rates per 10,000 residents. For each block, we take an inverse-distance-weighted average of the three closest reporting jurisdictions in the metro area (a procedure also used by Bishop and Murphy (2011)). We then average across blocks to obtain a neighborhood level measure of crime.

Table A3 in the appendix reports summary statistics for our amenity variables by city. Many of these amenity variables are correlated with one another at the neighborhood level. This motivated our parsimonious selection of amenity attributes; even so, correlation is re-

[15]Teacher-student ratios are also available but for only 58% of schools.

flected in our estimated weights on individual amenities. This collinearity is not a significant problem in our context, however, as our main goal is to derive an index of local amenities, not to derive willingness to pay estimates for each separate attribute.

4.3 Zoning Data

As an indicator of the restrictiveness of zoning Z, we use the Wharton residential land use regulatory index (WRI) (Gyourko et al. (2008)). These data have been widely used in peer-reviewed work for similar purposes. This index is based on surveys of local jurisdictions. We first use the metro-wide measure of zoning since the municipality with zoning/regulatory authority in most cases does not correspond to the school attendance boundary. In our view, the individual jurisdictions that respond to the survey are best thought of as a random sample representing their municipality, when appropriately weighted using sampling weights given by Gyourko et al. (2008). Appendix Table A3 includes the metro-level measure of the WRI for cities in our sample. As an alternative to the metro-wide index, we also place the school attendance boundaries in their corresponding municipality (by Census Place) rather than use the metro-wide average. This more precisely measures the regulatory environment for the neighborhood, although doing so significantly restricts the sample size because of non-responding municipalities and may introduce more measurement error.

The WRI is an aggregate of a variety of indicators, so in principle one can split land-use controls into those affecting minimum lot sizes and the number of lots. However, the message of Gyourko et al. (2008) is that rarely do cities seem to be substituting one type of regulation for another; rather, they either regulate a lot or a little on a variety of margins. Thus, the consensus in the literature using the WRI is that these subindices should not be drawn too finely. Accordingly, we will use the overall WRI in our main analysis. However, given our interest in contrasting restrictions on extensive margins to those of purchase of the intensive margin, we also will consider a lot size restrictions index separately from an "other regulations" measure constructed by subindices stripped of explicit density restrictions.

To gauge whether the WRI captures effects of regulations on housing, in Appendix Table A2, we compare within-neighborhood variance in property attributes to local regulation indices. We first decompose the variance to obtain the share of attribute (e.g., lot size) variance occurring within versus between neighborhoods in a municipality, and then pool the municipalities to run a regression of within-neighborhood variance on their WRI. We find that regulations to some extent homogenize the stock of housing within neighborhoods: a one-standard-deviation increase in regulation reduces within-neighborhood heterogeneity in property characteristics by about one-tenth of a standard deviation (depending on the attribute). Nevertheless, even in regulated areas, there is sufficient within-neighborhood variance in the attributes to elicit a housing services price.

Finally, one of our tests will augment the zoning data with estimates of housing stock growth from the U.S. Census Bureau.

5 Testing for Capitalization as a Two-Part Tariff

Section 3 suggested some testable implications of the existence of tickets. Our main strategy is first to recover the pieces of the two-part tariff pricing function (α and β) and then to describe the relationship between these prices and local amenities and how they vary with zoning.

5.1 Recovering Prices

The first step is to recover the "ticket" and "housing services" prices for each neighborhood. The basic hedonic regression (in levels) is

$$\frac{p_{cnit}}{I_{ct}} = \alpha_{cn} + \beta_{cn} h_c(L_i, x_i) + \epsilon_{cnit} \tag{14}$$

where p_{cnit} is the transaction price of property i, located in neighborhood n of city c, occurring at time t. I_{ct} is a time deflator from the FHFA.[16] The α_{cn} and β_{cn} terms are the variables of interest: respectively, the ticket and housing service prices. The housing service function is $h_c(L, x)$ (which may vary by city), a function of land (L) and of a vector of capital characteristics x.

Selecting the appropriate housing services function $h(\cdot)$ is a challenge both conceptually and practically. Conceptually, it is difficult to know precisely what constitutes "housing services" to households. Presumably, it includes land, living area, structure age (through quality, maintenance and aesthetics), and room partitioning (bedrooms, bathrooms, other rooms), but the exact functional form is unknown and is probably highly nonlinear. Thus, to estimate α and/or β in levels, the function $h(\ )$ either must be estimated or defined *a priori* by the econometrician. However, as we argue in more detail below, we can estimate patterns in α and β across neighborhoods under weaker assumptions.

We approach housing services in several ways. The first two approaches constrain β_{cn} to differ only for land while conditioning on the physical capital characteristics of the property:

$$\frac{p_{cnit}}{I_{ct}} = \alpha_{cn} + \beta_{cn} L_i + h_c(x_i) + \epsilon_{cnit}. \tag{15}$$

Here, we consider two variants of the control $h_c(x_i)$. One variant assigns a house with characteristics x_i in city c into the discrete categories for which we have estimates of the replacement cost of construction materials. We then assign $h_c(x_i)$ to be this replacement cost value and subtract it from the left hand side of the estimating equation. Similar approaches to isolating land prices have been used by Glaeser and Gyourko (2003), Glaeser and Gyourko (2005), Davis and Palumbo (2008) and others. We call this the "replacement cost" model. The other variant estimates $h_c()$ with flexible hedonic functions of the observed x. In particular, we use linear and quadratic terms for living area, dummy variables for age of structure (in decadal

[16] Our analysis at this stage is on cross-sectional property values, but of course these transact at different times, so we want to consider a constant index. As an alternative to the FHFA index, we also used a deflator estimated with our own data, finding similar results. We estimated $p_{cnit} = I_{ct}(\alpha_{cn} + \beta_{cn} h_c(x_i)) + \epsilon_{cnit}$ using non-linear regression on a subset of the data to recover $\hat{I}_{ct}$, which we then use to adjust the dependent variable in the remaining data.

bins), and dummies for the number of bedrooms, bathrooms, and/or total rooms (depending on the available information in each city). We call this the "hedonic" model.

These specifications allow local public goods to be capitalized into land prices as well as a ticket price. An obvious practical advantage of this assumption is ease of estimation: the lot size is observed, so we can simply make it an explanatory variable. Moreover, these forms are conceptually attractive in that land is the only truly immobile factor, so land capitalization is closest to the Ricardian sense (as in Scotchmer (1985)). However, this assumption rules out capitalization occurring in the physical structure of the property, which in reality is part of what comprise housing services. It assumes, for example, that a good school district is capitalized into a four-bedroom property (more fit for a family with children) and smaller two bedroom (more fit for a household without children) in the same way if they are on the same-sized parcel of land.

Therefore, we also consider more general models of housing services. The next approach walks back the structure of the first two, ignoring the capital characteristics entirely, so that $h_c(L_i, x_i) = L_i$. Clearly, this approach potentially has for an omitted variables problem. However, in addition to the advantage of parsimony, this formulation may be preferable to the first two if amenities are capitalized into housing characteristics x as well as land, and if lot size is correlated with housing services. In that case, it may be better to omit a researcher-defined $h(x)$ and simply take L as a proxy for $h_c(L, x)$. We call this approach the "land" model.

The remaining approaches allow for a flexible function of the property attributes, both land and capital, to form a housing services function. Whereas the models above can be estimated on a city-by-city basis, this variant requires estimating a generic function $h(L_i, x_i; \delta)$ (where δ is a parameter vector describing housing services as a function of observables x_i). Crucially, this function is consistent across cities, making it more challenging computationally.[17]

[17]The model requires joint estimation of $2N$ pricing parameters (a ticket and slope for each neighborhood), plus the δ parameters. Moreover, the model is nonlinear because the slope parameters are interacted with the

We first estimate the following equation with non-linear constraints on a small national subsample of the data:[18]

$$\frac{p_{cnit}}{I_{ct}} \;=\; \alpha_{cn} + \beta_{cn} h(L_i, x_i, \delta) + \epsilon_{cnit},$$

where $h(L, x, \delta)$ is a flexible function parameterized by δ. From this initial estimate, we obtain a consistent estimate of $h()$, which we denote $\hat{h}$. We then use the estimated $\hat{h}$ to impose that function on the remaining data and estimate α and β using

$$\frac{p_{cnit}}{I_{ct}} \;=\; \alpha_{cn} + \beta_{cn} \hat{h}(L_i, x_i) + \epsilon_{cnit}.$$

We call these the "estimated services" models.

We consider three functional forms for $h()$. The first and most lightly parameterized uses the natural log of living area and lot size and their interaction (three elements in δ). The second uses lot size and indicator variables for room partitions, including interactions between bedrooms and baths (26 elements in δ). The third extends the log lot size/living area polynomial to allow for vintage effects (i.e., structure age) in intercept and value per square foot of living space, and indicators for bathrooms (25 elements in δ).[19] Table A4 in the appendix reports some statistics on the fit of these models. They deliver very similar predictions of $h(L, x, \delta)$, though the last provides a marginally better goodness of fit.

function $h(x, \delta)$. For a model with K parameters in $h()$, this imposes $(K-1)(N-1)$ nonlinear restrictions. Because the scale and origin are not identified, the model is normalized by setting the slope parameter of one neighborhood to one and omitting the constant from $h()$. In practice, we found it most expedient to iterate between the linear subsets of the model–estimate the intercepts and slopes for a guess of δ, and then update δ using the new estimates of intercept and slope and so on, before proceeding to a nonlinear simplex estimation routine.

[18]We conduct a stratified sampling procure to generate the national subsample. This routine randomly selects two neighborhoods from each tercile of the price distribution for each metro area, then randomly selects the lesser of 120 or half the properties from within the neighborhood. This preserves a sufficient number of properties that the selected neighborhoods can remain in the main estimation. The resulting sample contained 62,250 properties from 612 neighborhoods (six neighborhoods from each of the 102 metro areas that survive to the second stage estimation).

[19]A practical consideration is that covariance in the observed housing attributes made it difficult to separately identify many parameters at once, and so parsimony was important for reliable convergence. For instance, it was difficult to obtain convergence for a model with indicators for bedrooms *and* a polynomial in living area, since these are correlated in the data.

Taking our model literally, under the functional form assumptions for $h()$, we can identify the price function $p(h)$, which we then assume is an affine transformation $p = \alpha + \beta h$. More generally, we cannot separately identify nonparameterically a generic price function $p()$ from a housing services function $h()$. We only know there is some composite $p(h())$. However, following the logic of Epple, Quintero, and Sieg (2018) and Landvoigt et al. (2015), we can still identify how between-city differences in G shift this function and whether the shift occurs more, on average, in intercept effects (α) or slope effects (β) with differences in regulation Z.

5.2 The Pricing of Local Public Goods

The second step is to relate these two components of pricing to local public goods and zoning. This involves using the price parameter estimates from the first stage and our measures of local amenities in neighborhoods. We estimate the following model using non-linear least squares:

$$\hat{\alpha}_{cn} = a_c + (1 + a_Z Z_c)\gamma' g_{cn} + \nu_\alpha \tag{16a}$$

$$\hat{\beta}_{cn} = b_c + (b_0 + b_Z Z_c)\gamma' g_{cn} + \nu_\beta. \tag{16b}$$

That is, we measure the relationship of both price components (α and β) to an index of local amenities $G = \gamma' g$, which is estimated from the data with a cross-equation restriction forcing it to be the same for both components. The a_c, b_c terms represent city dummies, which play a dual role. First, as usual, they capture city-wide characteristics in housing prices such as climate and labor-market conditions as well as the direct effects of land-use restrictions. Second, because we estimate housing services functions $h_c(\ )$ separately by city, we cannot separately identify differences in the scale of these services from the mean β in the city. The b_0 term captures the different way G is normalized into slopes (in dollars per 1000 square feet) relative to intercepts (dollars per lot).[20]

[20]Note that we cannot separately identify a_0, b_0, and the vector γ to scale, so we set $a_0 = 1$. Additionally, we cannot identify G to location separately from a_c, b_c, and b_0, so γ omits a constant term.

The a_Z, b_Z terms are the main variables of interest: They measure the interaction of local public goods with city-level land use restrictions Z. Our model predicts that places in which land use is heavily restricted will have more of their local public goods capitalized into ticket prices and less into the housing services slope. Hence, we expect $a_Z > 0, b_Z < 0$. Our approach relies on a differences-in-differences approach to identification. We do not seek to measure and are not able to identify the average effect of regulation on either component of housing prices. Rather, Equations (16a) and (16b) ask, among neighborhoods in more regulated cities, are prices more differentiated by G via α or β than among neighborhoods in less regulated cities?

As mentioned above, we treat Z both as a scalar (an overall measure of land use restrictions) and as a vector with two parts, an index of minimum lot size and restrictions that might constrain the number of lots. We will test the sensitivity of the second stage to alternative geographic levels of regulation, as well as non-regulatory proxies for neighborhood land frictions.

6 Results

We first explore the data for regularities that would be consistent with the presence of tickets without directly accounting for neighborhood amenities. We then proceed to the formal test of amenity capitalization via tickets.

6.1 Residuals in the Proportional Pricing Model

Section 3 illustrated how ticket capitalization would bias the semilog price model of housing services: residuals would be downward sloping in $h()$ for high-price neighborhoods, but upward sloping in $h()$ for low-price neighborhoods (see Figure 8). We test for this pattern in the price data for our sample of cities. First, we estimate the standard log-price model with neighborhood dummies and a flexible function of property attributes, recovering the

Table 3: Residuals from Log Price Hedonic Model

Quality Ranking Method:	Raw Median Price	Estimated Coefficient
	1	2
Residuals by Neighborhood Quality Ranking (NQR)		
NQR X Small Properties	0.279	0.248
	(0.0007)	(0.0007)
NQR X Large Properties	-0.240	-0.232
	(0.0007)	(0.0007)
Large Property Intercept	0.660	0.639
	(0.0006)	(0.0006)
Constant	-0.339	-0.323
	(0.0004)	(0.0004)

NOTES: The left-hand-side variable is the residual from the semi log hedonic model. Standard errors in parentheses. Source: Authors' calculations using housing transactions data described in Section 4.

projected prices and the residual. (Recall that in this case, unlike our αs, the dummies capture proportionate effects.) As a descriptive exercise, we then regress these residuals on how "large" the property is (indicated by a dummy for whether or not it is in the top half of the within-neighborhood price ranking) and how "nice" the neighborhood is (indicated by its between-neighborhood price ranking) and the interaction of the two. This brings the test illustrated by Figure 8 to actual data spanning multiple regions of the country.

The results are reported in Table 3. The first column ranks neighborhoods by raw median prices, whereas the second column ranks them by the estimated coefficient on the neighborhood dummy variable in the log-price hedonic. In both cases, we see the pattern predicted by Figure 8: the residual on small properties grows in the neighborhood ranking–i.e., over prediction in inexpensive (presumably low-g) neighborhoods–while the residual for large properties shrinks in the price ranking–i.e., over prediction in expensive (presumably high-g) neighborhoods. This is not a sufficient test of *capitalization*, as we have introduced no information on amenities, but the pattern in residuals indicates that neighborhoods are stratified in part by shifts to the pricing function: tickets are present. As discussed in Section 3, this serves as a cautionary tale for use of proportional pricing (including log-transformed) models of neighborhood pricing.

Table 4: Tests of Equivalence in Intercept and Slope Parameters: Counts of Metro Areas

Model:	Replace Cost	Hedonic	Land	Estimated Services:		
				Land, Area	Land, Rooms	4 + Vintage, Bath
	1	2	3	4	5	6
Metro Count	96	104	104	103	103	103
Coefficient: α_n						
p-value < 0.01	93	97	99	89	98	96
p-value > 0.01	3	7	5	14	5	7
Coefficient: β_n						
p-value < 0.01	94	102	101	97	97	101
p-value > 0.01	2	2	3	6	6	2

NOTES: The figures in the table are counts of cities whose statistical test of equivalence for the α (intercept) and β (slope) parameters across neighborhoods within the city fall within the specified p-values. See Sections 4 and 5 for detailed definitions. Source: Authors' calculations using housing transactions data described in Section 4.

6.2 Recovered Housing Price Components

Next, we test whether the components of the housing price function, the intercept and slope terms, α and β, are important for neighborhood price heterogeneity. That is, we test the null hypothesis that the intercepts are the same (but not necessarily zero) across all neighborhoods within each metro area, and similarly for the equivalence of the estimate slope coefficients. Rejecting the former hypothesis is evidence for local pricing via tickets and the latter for slopes.

In Table 4, we report counts of metro areas with statistically significantly different estimates of α and β. We find statistical evidence for pricing via both dimensions. In nearly all cities, we reject the hypothesis that all neighborhoods have the same housing price intercept at standard p-values, and likewise for the slope parameters.[21]

We view this as a test of the minimal necessary implications of our model, as evidence that some form of neighborhood pricing occurs through each component of the housing price

[21] In most cases, failure to reject the null results from an apparent lack of statistical power. For example, the the hedonic-adjusted model (column 3), the cities we fail to reject equivalence of α are Columbia, SC, Huntsville, AL, Mobile, SC, Myrtle Beach, SC, Tulsa, OK, Denver, CO, and Saint Louis, MO. Only the last two major metro areas have a large number of neighborhoods to compare. Also, the failure-to-reject cities exhibit failure in both coefficients and across all models, indicating poor precision in the recovery of Equation (14) more so than a rejection of the capitalization model.

function. However, we also acknowledge that this test of particular values of the αs and βs is based partly on functional form restrictions. Accordingly, next we consider how the αs and βs *shift* with differences in differences in amenities and frictions to configuration.

Table A5 in the appendix reports summaries of the first stage estimates by metro area.

6.3 The Pricing of Local Public Goods

6.3.1 Metro Level Regulation

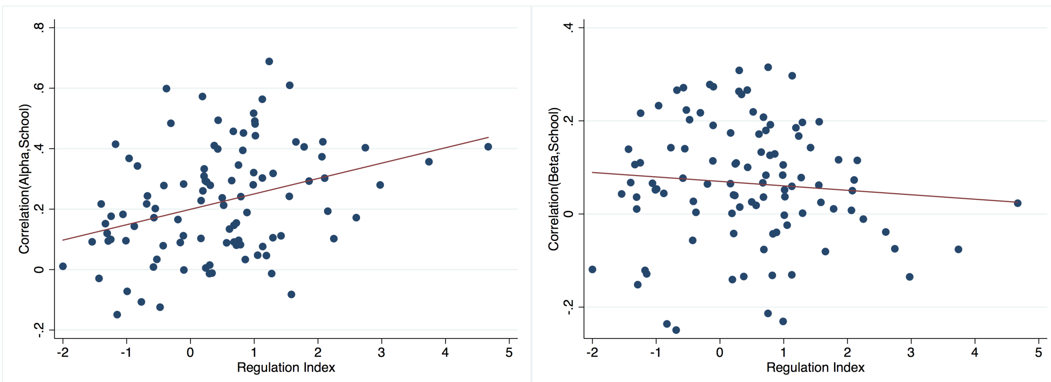
Our basic hypothesis is that the capitalization of amenities will occur more in tickets and less in housing services at the intensive margin where land-use restrictions are higher. As a descriptive way of thinking about this, we first look at the correlation between α and school test scores across neighborhoods within a city and likewise the correlation between β and test scores. We then plot each city's correlation coefficient against its WRI. Figure 9 displays the results of this exercise. The top two figures are the correlations for α and β, respectively, using the "hedonic model" in the first stage, in which we control for structural housing characteristics but allow capitalization of G only into land. The bottom two figures similarly use the housing services model with capitalization into land and living area. Both models tell the same story: in areas with high regulation, there is a higher correlation between school quality and tickets, and a slightly lower correlation between school quality and the price of land and/or housing services. This pattern is consistent with our model.

More formally, our main empirical test of the model is through the regression model of (16a), (16b), using estimates from the first stage model, (15). The results from the second stage regressions are presented in Table 5. All the reported specifications use the FHFA index to deflate prices in the first step and use heteroskedastic-robust standard errors. Each column of the table, and similar tables that follow, uses a different definition of housing services, as described above.

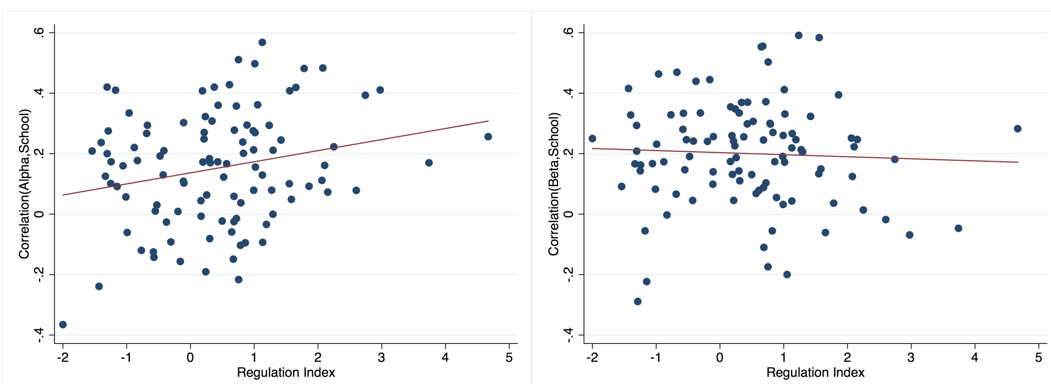
The first two columns present the specifications putting capitalization into land but controlling for capital characteristics, what we have termed the construction cost (column 1)

Figure 9: Within-Metro Correlation of School Quality to Estimated α, β to Metro Regulation

Hedonic Model



Estimated Services Model: Land, Living Area



Source: Authors' calculations using housing transactions data, SABINS attendance zone data, and school test scores data, described in Section 4.

Table 5: Second Stage Regression of Tickets and Slopes: Metro Level Regulation Index

Model:	Replace Cost	Hedonic	Land	Estimated Services:		
				Land, Area	Land, Rooms	4 + Vintage, Bath
	1	2	3	4	5	6
N	19,543	19,892	19,889	19,893	19,912	19,881
A: Price Decomposition Coefficients						
a_Z	0.328	0.390	0.144	0.335	0.242	0.265
	(0.037)	(0.037)	(0.016)	(0.057)	(0.023)	(0.029)
b_0	0.017	0.026	-0.011	0.044	0.016	0.014
	(0.035)	(0.034)	(0.019)	(0.05)	(0.022)	(0.028)
b_Z	-0.005	-0.001	0.000	0.003	0.003	0.000
	(0.028)	(0.028)	(0.016)	(0.044)	(0.019)	(0.024)
B: Local Amenities Coefficients, γ						
Test Scores: Math	29,494.50	24,636.71	48,182.32	13,535.36	36,673.12	24,018.57
	(1142.83)	(909.69)	(1014.55)	(917.98)	(930.8)	(837.04)
Dist. to CBD	-1,277.64	-869.98	-98.80	178.77	-1,991.23	48.06
	(59.12)	(44.12)	(52.33)	(47.14)	(57.19)	(43.49)
CERCLA Sites	-3,987.70	-2,986.66	-18,407.25	-836.33	1,226.10	-4,976.05
	(1715.85)	(1405.37)	(2028.91)	(1727.41)	(1754.07)	(1599.67)
Ozone	-647.06	-569.09	-685.79	-75.36	-1,167.11	-235.91
	(82.12)	(65.48)	(95.62)	(83.85)	(84.45)	(79.18)
Crime	0.70	-2.33	-11.84	-5.26	-0.25	-7.01
	(0.54)	(0.42)	(0.58)	(0.53)	(0.48)	(0.48)
Composite Local Amenity Index, $\gamma' g$						
Std. Dev.	103,256.30	71,501.14	49,508.18	21,740.93	159,884.10	25,938.09
Interquartile Range	34,125.99	30,156.31	65,059.39	21,924.29	46,854.17	33,735.01

NOTES: Huber-White standard errors in parentheses. Observations are weighted by the inverse of the variance of the first-step estimator. Outliers more than five standard deviations from the mean are excluded, and neighborhoods per specifications will vary accordingly. Source: Authors' calculations using housing transactions data, SABINS attendance zone data, local amenities data, and WRI land use regulation data, all described in Section 4.

and hedonic (2) methods. The top panel shows the coefficients decomposing α and β. The primary coefficient of interest, a_z is positive, at 0.33 for the replacement cost and 0.39 for the hedonic method, and statistically different from zero. This indicates that, as conjectured, more highly regulated metropolitan areas have neighborhoods that differ by intercepts. This is precisely what our model predicts. On the other hand, the coefficient on land slope capitalization, b_z, is slightly negative, which would indicate a downward tilting to the land-slope in more regulated areas with more ticket capitalization, although this is very imprecisely estimated and not robust across specifications, so we do not draw firm conclusions from these point estimates.

The next panel reports coefficients on the index of amenities. While we do not present these as estimates of willingness to pay, it is reassuring that the coefficients are sensible: test scores are a "good" and increase prices, whereas distance from the central city, environmental pollution, and crime are disamenities, depressing prices.[22] At the bottom of the table, we report the standard deviation and interquartile range of our estimated G index, $\gamma' g$.

The third column uses the most parsimonious definition of housing service, the land-only model without any controls for capital. Under this method, we find the regulatory interaction term a_z to be 0.14 and still statistically significant. The scale coefficient converting the amenities index between intercept shifts and prices per square foot of land, b_0, is a negative at point estimate, although not statistically significant from zero. This creates some counterintuitive interpretations of magnitude, but given the potentially severe omitted variables problem in this specification, we do not take the point estimate too literally. This specification is our least preferred.

Finally, columns 4 to 6 present the specifications in which housing services were derived from an index estimated in an initial stage. While these introduce much greater flexibility to the capitalization function, they return very similar results as the previous specifications. The a_z estimates range from 0.24 to 0.34, indicating an important role for tickets shifting the capitalization function between neighborhoods, even when capitalization per unit of service can come via an amalgamation of capital and land.

To interpret their magnitude, the coefficients can be converted to the share of a price difference between neighborhoods (with different G) that is attributable to tickets, $\frac{\partial p}{\partial G} = \frac{1+a_z Z}{1+a_z Z+b_0 h+b_z Z h}$. The denominator is the total effect on housing prices for a marginal change in G, whereas the numerator is just the portion through tickets. This value will depend on the amount of housing services h as well as the level of land-use regulation Z. In Panel A of Table 6 we report the value at the median lot size in the data and at three levels of regulation. The

[22] Because the underlying variables are on different scales, the coefficient sizes cannot be directly compared with one another. In unreported regressions, we find the school quality component accounts for two-thirds to four-fifths of the variance in the index, and about 80 percent of the variance is between neighborhoods, within metro areas.

Table 6: Implied Pricing Patterns: Metro Level Regulation Index

Model:	Replace Cost	Hedonic	Land	Estimated Services:		
				Land, Area	Land, Rooms	4 + Vintage, Bath
	1	2	3	4	5	6
A: Implied Ticket Share of Price Changes [i]						
Low Reg. (Z=-1)	0.800	0.754	1.103	0.685	0.880	0.878
Med. Reg. (Z=0)	0.887	0.838	1.088	0.751	0.891	0.906
High Reg. (Z=1)	0.939	0.881	1.078	0.789	0.898	0.924
B: Increase In Ticket Price, Low G N'hood to High G N'hood (Share of Property Value, by Regulatory Regime and Property Size [ii])						
Low / Small	0.087	0.095	0.199	0.048	0.079	0.076
Low / Med.	0.086	0.088	0.184	0.047	0.077	0.075
Low / Large	0.077	0.074	0.161	0.046	0.073	0.072
High / Small	0.186	0.246	0.285	0.101	0.136	0.138
High / Med.	0.182	0.226	0.262	0.100	0.133	0.136
High / Large	0.162	0.186	0.227	0.096	0.126	0.132

NOTES: This table uses point estimates from Table 5. [i] Derived using $\frac{\partial p}{\partial G} = \frac{1+a_z Z}{1+a_z Z+b_0 h(\cdot)+b_z Z h(\cdot)}$ where $h(\cdot)$ is measured at the median level of housing service. [ii] The increase in ticket value, from change across inter-quartile range of composite amenity index, expressed as a proportion of the value of a property offering housing services at the 25^{th} (small), 50^{th} (medium), or 75^{th} (large) percentiles. Housing service percentiles are calculated at the metro level, and the table reports the average across metro areas. Source: Authors' calculations using estimates from Table 5.

implied ticket share of between-neighborhood price differences ranges from 0.69 to 0.88 for low-regulation cities and 0.79 to 0.94 in high-regulation cities. To the extent we can identify ticket levels using our functional form, this finding underscores the importance of tickets for explaining capitalization in a variety of regulatory environments. More importantly, going down the three rows, we also see that the values are increasing, indicating that tickets play an increasingly important *relative* role for explaining capitalization as land-use regulations tighten.[23]

Panel B of the table interprets the results by posing the question, what is the change in ticket value from a low-G neighborhood to a high-G neighborhood in lightly regulated cities compared with highly regulated cities? To operationalize a calculation, we use a change from the 25^{th} percentile of estimated G distribution to the 75^{th} percentile in a city with $z = -1$ compared with a city with $z = 1$. To normalize to regional price differences, we present the

[23] In column 3, using the point estimates of the land-alone housing services function, the implied shares are actually greater than one and decreasing in regulation. This is because the point estimate of the scaling coefficient, b_0, is negative, which as noted we treat with some skepticism.

change in ticket values between neighborhoods as shares of the value of properties of small, medium, or large size (25^{th}, 50^{th}, or 75^{th} percentile of housing services, respectively). In a lightly regulated city, moving to a higher-G neighborhood will increase ticket expenditure at a rate of 5 to 20 percent of the property value, depending on the specification (and 5 to 10 in our preferred specifications). In a highly regulated city, the change is about twice as large–the higher-G neighborhood will have a more expensive ticket representing an additional 10 to 25 percent of the value of the property. Naturally, the ticket expenditure makes up a smaller proportion of larger properties offering more housing service. Thus, in virtually all cities, the differences in entry ticket cost between neighborhoods comprise a substantial portion of the differences in housing expenditure, and importantly, this pattern is especially strong in highly regulated cities.

6.3.2 Municipal Level Regulation

Next, we allow land-use regulations to vary at the municipal level rather than the metro level. The advantage here is that most regulations are actually imposed by the municipality, so we gain a more geographically precise measure of what the regulatory regime actually is. For example, the city of Los Angeles and the city of Santa Monica have separate regulatory authority within the same metro area. The primary disadvantage is that this precision comes at a substantial loss of the sample because not every municipality within the metro area is covered by the WRI survey. Additionally, if survey responses from individual jurisdictions are noisy measures of the underlying regulatory stringency, using micro-level data rather than group averages will increase measurement error.

Empirically, the exercise is very similar to the metro level regressions, except that now we must consider the potential direct effects of regulation on prices via tickets or slopes. In the main model, metro-level fixed effects accounted for the direct effects of regulation. In principle, we could use municipal level fixed effects, but in practice the number of municipalities makes this computationally intractable in a nonlinear model. Instead, we account for direct effects by allowing the submetro level of regulation to shift the metro level intercept by introducing one more coefficient to each equation, so that the specification is now, for jurisdiction j,

$$\hat{\alpha}_{cn} = a_c + a_Z^1 Z_{cj} + (1 + a_Z^2 Z_{cj})\gamma' g_{cn} + \nu_\alpha \tag{17a}$$

$$\hat{\beta}_{cn} = b_c + b_Z^1 Z_{cj} + (b_0 + b_Z^2 Z_{cj})\gamma' g_{cn} + \nu_\beta, \tag{17b}$$

where a_Z^1 and b_Z^1 now capture the direct effects of regulation in j and, as before, a_Z^2 and b_Z^2 capture the effects of regulation on the capitalization of G.

Table 7 reports the results with columns ordered as before. The results are qualitatively similar to the metro level results. The main coefficient of interest, a_Z^2, which captures the extent to which G is capitalized into tickets more in higher-regulation areas, is positive and statistically significant in all models. Comparing it with a_Z in Table 5, we see it is somewhat lower in magnitude at the municipality level than at the metro level, except for the land-only model (column 3). The coefficient b_Z^2, which captures the extent to which G is differentially capitalized into unit housing services in higher-regulation areas, continues to be small in (absolute) magnitude and statistically insignificant. The direct effect of zoning, measured by coefficients a_z^2, b_z^2, is seen to increase housing prices via both the extensive and intensive margin, consistent with the literature on the effect of regulation on housing supply (e.g., Glaeser and Gyourko (2003), Quigley and Raphael (2005), Saiz (2010), Saks (2008)), although our approach is less suitable than others for making causal statements on the direct effects. (We are focused on the within-city phenomenon of regulation shifting the neighborhood price functions.)

Table 8 again helps interpret these coefficients. As in the metro level zoning model, tickets are quantitatively important, accounting for two-thirds or more of the change in prices from a change in G. Generally, the magnitude of the ticket share increases with regulatory intensity. (However, in some models, the point estimate on b_Z is also positive, so the ticket share of

Table 7: Second Stage Regression of Tickets and Slopes: Municipal Level

Model:	Replace Cost	Hedonic	Land	Estimated Services:		
				Land, Area	Land, Rooms	4 + Vintage, Bath
	1	2	3	4	5	6
N	9,355	9,500	9,498	9,505	9,513	9,498
A: Price Decomposition Coefficients						
α_z	0.124	0.192	0.098	0.040	0.053	0.061
	(0.014)	(0.023)	(0.01)	(0.009)	(0.005)	(0.007)
β_z	-0.239	-0.041	0.005	0.133	0.035	0.129
	(0.348)	(0.382)	(0.218)	(0.534)	(0.308)	(0.494)
a_Z	0.111	0.219	0.278	0.136	0.051	0.199
	(0.018)	(0.027)	(0.024)	(0.049)	(0.008)	(0.031)
b_0	0.020	0.032	-0.016	0.069	0.015	0.026
	(0.053)	(0.049)	(0.031)	(0.071)	(0.025)	(0.037)
b_Z	-0.003	-0.002	0.000	0.013	0.000	0.007
	(0.017)	(0.018)	(0.026)	(0.054)	(0.008)	(0.029)
B: Local Amenities Coefficients, γ						
Test Scores: Math	33,157.45	29,613.24	49,067.07	12,703.37	44,385.45	24,190.21
	(1557.32)	(1246.19)	(1366.43)	(1264.26)	(1312.54)	(1078.69)
Dist. to CBD	-1,477.01	-1,103.30	-36.71	-381.67	-2,380.08	-369.75
	(103.88)	(82.33)	(71.18)	(95.04)	(96.97)	(74.15)
CERCLA Sites	-8,867.64	-2,336.09	-13,991.75	7,162.30	-4,115.51	-707.67
	(3641.41)	(2914.63)	(3338.04)	(3210.57)	(3491.71)	(2714.54)
Ozone	-1,260.24	-1,219.47	-1,110.02	-239.44	-1,930.36	-438.22
	(186.97)	(146.01)	(154.94)	(176.89)	(189.34)	(146.31)
Crime	8.67	4.02	-5.99	-4.92	6.42	-5.87
	(1.15)	(0.83)	(0.9)	(0.91)	(0.95)	(0.76)
Composite Local Amenity Index, $\gamma' g$						
Std. Dev.	119,879.00	90,274.98	45,259.44	33,329.09	191,426.70	37,336.53
Interquartile Range	41,580.40	33,939.00	59,721.51	19,853.39	56,223.41	32,676.97

NOTES: Huber-White standard errors in parentheses. Observations are weighted by the inverse of the variance of the first-step estimator. Outliers more than five standard deviations from the mean are excluded, and neighborhoods per specifications will vary accordingly. Source: Authors' calculations using housing transactions data, SABINS attendance zone data, local amenities data, and WRI land use regulation data, all described in Section 4.

Table 8: Implied Pricing Patterns: Municipal Level

Model:	Replace Cost	Hedonic	Land	Estimated Services:		
				Land, Area	Land, Rooms	4 + Vintage, Bath
	1	2	3	4	5	6
A: Implied Ticket Share of Price Changes [i]						
Low Reg. (Z=-1)	0.836	0.752	1.194	0.672	0.897	0.847
Med. Reg. (Z=0)	0.870	0.806	1.135	0.659	0.900	0.836
High Reg. (Z=1)	0.898	0.845	1.104	0.650	0.902	0.828
B: Increase In Ticket Price, Low G N'hood to High G N'hood (Share of Property Value, by Regulatory Regime and Property Size [ii])						
Low / Small	0.135	0.132	0.141	0.058	0.118	0.081
Low / Med.	0.132	0.122	0.131	0.058	0.115	0.080
Low / Large	0.117	0.103	0.116	0.056	0.110	0.078
High / Small	0.170	0.212	0.269	0.079	0.132	0.127
High / Med.	0.166	0.197	0.249	0.078	0.129	0.125
High / Large	0.147	0.166	0.218	0.076	0.122	0.121

NOTES: This table uses point estimates from Table 7. [i] Derived using $\frac{\partial p}{\partial G} = \frac{1+a_z Z}{1+a_z Z+b_0 h(\cdot)+b_z Z h(\cdot)}$ where $h(\cdot)$ is measured at the median level of housing service. [ii] The increase in ticket value, from change across inter-quartile range of composite amenity index, expressed as a proportion of the value of a property offering housing services at the 25^{th} (small), 50^{th} (medium), or 75^{th} (large) percentiles. Housing service percentiles are calculated at the metro level, and the table reports the average across metro areas. Source: Authors' calculations using estimates from Table 7.

the derivative $\frac{\partial p}{\partial G}$ falls slightly with increased Z. Yet the estimated values of b_Z^2 are not statistically different from zero, so we are reluctant to draw conclusions from these cases.) In Panel B, we see that price increases from such a change in G are eight to 27 percent higher in more regulated cities at a fixed house size and are higher as a proportion for smaller houses at a fixed level of regulation. These patterns are consistent with our predictions.

Overall, the municipal level results are consistent with that of the metro level regression. Capitalization via tickets is important everywhere, but especially so in highly regulated environments.

6.3.3 Multiple Regulatory Indices

The WRI is an aggregated index of many forms of regulation. Most of these make the process of constructing new housing more burdensome (e.g., length or number of review processes) or otherwise more expensive (e.g., taxes and impact fees) and may reduce the amount of new units constructed, ceteris paribus. But one subindex index stands out: Restrictions on the minimum allowable lot size. This is a literal constraint on the amount of land consumed per housing unit and has been the focus of much of the fiscal zoning literature. In the theory section, we distinguished between minimum purchase requirements, which induce a two part tariff on constrained individuals within a neighborhood, and quantity restrictions on the maximum number of lots, which induce an extensive margin price to the neighborhood at large. We next apply our empirical test of ticket capitalization to separate indices of regulatory difficulty and of minimum lot size. Our theory predicts greater interaction effects for the former than for the latter.

In particular, we re-estimate the second stage (Equations (17a) and (17b)) but with two regulation indices: one an adjusted-WRI "other regulations" index purged of restrictions on minimum lot size and one for the existence of minimum lot size requirements, an indicator function.[24] We focus on the municipal level regression, despite the loss of sample size, in favor of using the more precise survey response for the minimum lot size subindex, although the metro level results are quite similar. It is worth noting that while most subindices are correlated within cities (i.e., cities tend to regulate highly or not and do not appear to substitute one form for another, as explained by Gyourko, Saiz, and Summers (2008)), minimum lot size is nearly uncorrelated with the other regulations index.

Table 9 reports results from these models. Panel A reports the pricing function decomposition coefficients. The positive coefficient of $a_{other\,regs}$ indicates that cities with greater regulatory burden exhibit more capitalization via tickets. Minimum lot size requirements, however, do not induce more ticket-based capitalization, as the $a_{lotsize}$ coefficient is actually negative and typically imprecisely estimated across specifications. This result is consistent with the prediction of the theory in Section 2. It is the general regulatory burden driving the ticket capitalization results found earlier and not minimum lot sizes explicitly.

[24]Variants of this sub-index, including the level of the minimum lot size (in acres) and the existence of minimum size larger than some threshold, return similar results. The full WRI generated by Gyourko, Saiz, and Summers (2008) uses as input subindex an indicator function for minimum lot sizes larger than two acres.

Table 9: Second Stage Regression of Tickets and Slopes: Multiple Regulatory Indices, Municipal Level Regulations

Model:	Replace Cost	Hedonic	Land	Estimated Services:		
				Land, Area	Land, Rooms	4 + Vintage, Bath
	1	2	3	4	5	6
N	9,355	9,500	9,498	9,505	9,513	9,498
A: Price Decomposition Coefficients [i]						
$a_{other\ regs}$	0.150	0.319	0.397	0.221	0.070	0.270
	(0.022)	(0.035)	(0.035)	(0.059)	(0.01)	(0.04)
$a_{lotsize}$	-0.061	-0.058	-0.029	-0.111	-0.024	-0.036
	(0.019)	(0.023)	(0.053)	(0.057)	(0.009)	(0.048)
b_0	0.014	0.032	-0.011	0.063	0.015	0.026
	(0.051)	(0.051)	(0.064)	(0.078)	(0.026)	(0.051)
$b_{other\ regs}$	0.000	-0.003	0.000	0.010	0.001	0.009
	(0.017)	(0.022)	(0.033)	(0.06)	(0.009)	(0.036)
$b_{lotsize}$	0.002	-0.001	-0.006	0.004	0.000	0.000
	(0.02)	(0.023)	(0.072)	(0.055)	(0.009)	(0.047)
B: Local Amenities Coefficients, γ						
Test Scores: Math	35,220.38	31,209.92	50,492.89	13,669.47	45,469.93	24,859.45
	(1691.29)	(1399.78)	(2496.43)	(1478.52)	(1380.41)	(1430.61)
Dist. to CBD	-1,439.73	-1,085.87	-10.13	-421.19	-2,395.42	-359.88
	(105.8)	(84.41)	(64.36)	(95.7)	(99.92)	(74.87)
CERCLA Sites	-9,319.44	-2,251.85	-13,901.55	7,184.76	-3,983.71	-806.06
	(3759.68)	(2961.35)	(3383.22)	(3386.75)	(3558.06)	(2762.69)
Ozone	-1,220.18	-1,144.50	-1,011.87	-314.16	-1,910.19	-416.33
	(196.89)	(151.76)	(164.73)	(192.01)	(195.66)	(153.29)
Crime	8.78	4.12	-4.83	-5.12	6.44	-5.65
	(0.99)	(0.81)	(0.88)	(0.93)	(0.96)	(0.77)
Composite Local Amenity Index, $\gamma' g$						
Std. Dev.	117,259.50	89,145.48	45,375.08	36,535.36	192,717.20	36,904.26
Interquartile Range	42,708.70	34,969.40	59,416.25	21,263.28	57,031.90	33,038.80

NOTES: Huber-White standard errors in parentheses. Observations are weighted by the inverse of the variance of the first-step estimator. Outliers more than five standard deviations from the mean are excluded, and neighborhoods per specifications will vary accordingly. [i] The coefficients measuring direct effects are suppressed for readability, but are available on request. Source: Authors' calculations using housing transactions data, SABINS attendance zone data, local amenities data, and WRI land use regulation data, all described in Section 4.

6.3.4 History as Friction: Path Dependence

As we noted at the outset, land-use restrictions need not be confined to government regulations. Anything that prevents the addition of housing units by subdividing lots or by building multiple units on a lot could create tickets, including historical development patterns that get locked in over time. Accordingly, we might expect relatively more capitalization of G into tickets in older cities, which developed a long time ago, and more capitalization in housing services in more recent cities. To test this possibility, we re-estimate Equations 17a and 17b, using county-level growth rates in the housing stock from 1980-2010 instead of the WRI, controlling for those growth rates in levels as well as city dummies. We use county-level data here so that we can match jurisdiction boundaries over the thirty-year period. The larger spatial average and longer time window also reduce concern about the simultaneity of growth and ticket prices.

Table 10 displays the results, in the first panel for a model using the log of the 1980-2010 growth rate in the housing stock. (For brevity, we omit reporting coefficients on our $\gamma' g$ index here, but they are available upon request.) The second panel displays results for a dummy variable indicating whether the county had a growth rate of more than 50 percent in its housing stock.[25] The key variable of interest is a^2_{growth}, which we expect to be negative (less capitalization into tickets in counties with a younger housing stock). We find this pattern holds for both panels except column 3 (land-only) and for the final column, where it is not statistically significant.

The next two panels replicate the first two models but include land-use regulations through the WRI as well as housing growth. This could be important to distinguish, as low growth could be the result of restrictive land regulations. Again, the patterns we have found hold up. The variable a_Z, which represents, as in our base models, how the WRI index affects capitalization of G into tickets, is positive and statistically significant in all models. In itself, it is higher than in our base models as well, but we also see that capitalization into

[25] Besides integer convenience, 50 percent is approximately the median growth rate by counties: the unweighted growth rate is 43 percent while the population-weighted growth rate is 57 percent.

tickets is reduced in younger counties, as in the first two panels, again accept for columns 1 and 2.

6.4 Tickets and Price Appreciation

Having established that, cross-sectionally, prices between neighborhoods differ more in intercepts in heavily regulated areas and more in average slope in lightly regulated areas, we extend our analysis to examine the role of each part (tickets and slopes) in housing price dynamics. In this last exercise, we ask, when housing markets cycle, is it the extensive or intensive margin prices that fluctuate?

To study the components' cyclical dynamics, we expand our sample of housing transactions to 2000 (or the first available year, no later than 2003) until 2011. We mark the periods of high and low prices for each metro area using the FHFA index, splitting the data by the quarter of maximum three-year price growth. Using the metro level break point in price growth–typically around 2004–prices are "low" before and "high" after. Data periods after the Great Recession are also included as "low" if prices stabilized after declining–a point arising around 2009-2010, if at all. These additional data requirements limit the available metro areas to 97. We then run an un-deflated version of Equation (14). Here, we use the hedonic method to adjust for capital so we can decompose appreciation into tickets, land slopes, and capital prices. Finally, we use the estimated coefficients to project prices for standardized properties at the $25^{th}, 50^{th}$, and 75^{th} percentile of the lot size distribution for each metro area.

The first column of Table 11 shows that the average neighborhood exhibited 40 percent price appreciation, roughly the same across properties of different size.[26] The next three columns report the appreciation (in percentage points) accounted for by tickets, land, and capital, respectively. Note that these are all scaled by the low period property value so that they have the same denominator for each property size and therefore sum to the first column

[26] We trim extreme outliers in neighborhood appreciation to avoid skewness affecting the means.

Table 10: Second Stage Regression of Tickets and Slopes: Growth in the Housing Stock

Model:	Replace Cost	Hedonic	Land	Estimated Services:		
				Land, Area	Land, Rooms	4 + Vintage, Bath
	1	2	3	4	5	6
A: Log County Growth Rate						
a^1_{growth}	-0.209	0.037	0.012	0.039	-0.154	0.000
	(0.019)	(0.012)	(0.007)	(0.007)	(0.007)	(0.006)
b^1_{growth}	-0.977	-0.200	-0.458	-0.371	-0.171	-0.759
	(1.272)	(0.516)	(0.284)	(0.654)	(0.399)	(0.784)
a^2_{growth}	-0.270	-0.046	0.044	-0.116	-0.297	0.023
	(0.03)	(0.019)	(0.01)	(0.039)	(0.02)	(0.015)
b_0	-0.005	0.021	-0.003	0.062	0.016	0.014
	(0.023)	(0.026)	(0.018)	(0.06)	(0.02)	(0.027)
b^2_{growth}	-0.022	0.002	0.006	0.006	-0.004	-0.002
	(0.023)	(0.024)	(0.014)	(0.036)	(0.017)	(0.017)
B: I(High County Growth Rate)						
a^1_{growth}	-0.287	0.018	-0.057	0.030	-0.188	-0.029
	(0.018)	(0.032)	(0.013)	(0.016)	(0.007)	(0.011)
b^1_{growth}	-0.556	-0.083	-0.300	-0.216	-0.211	-0.453
	(0.614)	(0.735)	(0.371)	(0.73)	(0.438)	(0.518)
a^2_{growth}	-0.413	-0.116	0.055	-0.524	-0.364	-0.071
	(0.028)	(0.038)	(0.029)	(0.053)	(0.02)	(0.041)
b_0	0.018	0.016	-0.017	0.030	0.015	0.016
	(0.028)	(0.032)	(0.023)	(0.041)	(0.019)	(0.028)
b^2_{growth}	-0.021	0.004	0.012	-0.003	-0.004	-0.006
	(0.032)	(0.041)	(0.031)	(0.06)	(0.024)	(0.041)
C: Log County Growth Rate, w/ zoning						
a^1_{growth}	-0.205	0.044	0.013	0.040	-0.146	0.001
	(0.019)	(0.012)	(0.007)	(0.007)	(0.006)	(0.006)
b^1_{growth}	-0.843	-0.217	-0.458	-0.331	-0.166	-0.750
	(1.185)	(0.508)	(0.283)	(0.617)	(0.391)	(0.778)
a^2_{growth}	-0.332	-0.091	0.038	-0.198	-0.329	0.002
	(0.042)	(0.027)	(0.011)	(0.06)	(0.025)	(0.018)
a^2_z	0.635	0.720	0.221	0.886	0.420	0.444
	(0.079)	(0.073)	(0.026)	(0.162)	(0.047)	(0.051)
b_0	0.004	0.031	-0.003	0.090	0.017	0.017
	(0.043)	(0.041)	(0.022)	(0.093)	(0.029)	(0.036)
b^2_{growth}	-0.030	0.004	0.007	0.009	-0.004	-0.003
	(0.032)	(0.032)	(0.015)	(0.049)	(0.02)	(0.02)
b^2_z	-0.011	-0.004	-0.001	0.005	0.003	-0.001
	(0.056)	(0.052)	(0.026)	(0.105)	(0.038)	(0.042)
D: I(High County Growth Rate), w/ Zoning						
a^1_{growth}	-0.274	0.094	-0.061	0.024	-0.180	-0.032
	(0.018)	(0.035)	(0.013)	(0.016)	(0.007)	(0.011)
b^1_{growth}	-0.547	-0.111	-0.297	-0.202	-0.206	-0.452
	(0.617)	(0.724)	(0.371)	(0.714)	(0.434)	(0.517)
a^2_{growth}	-0.482	-0.333	0.015	-0.631	-0.418	-0.161
	(0.035)	(0.043)	(0.03)	(0.067)	(0.023)	(0.046)
a^2_z	0.397	0.600	0.233	0.543	0.295	0.441
	(0.044)	(0.053)	(0.026)	(0.077)	(0.028)	(0.046)
b_0	0.027	0.019	-0.017	0.037	0.015	0.018
	(0.036)	(0.04)	(0.025)	(0.051)	(0.022)	(0.033)
b^2_{growth}	-0.026	0.005	0.014	0.004	-0.005	-0.007
	(0.041)	(0.05)	(0.033)	(0.074)	(0.027)	(0.047)
b^2_z	-0.004	-0.002	-0.003	0.003	0.002	0.001
	(0.035)	(0.041)	(0.027)	(0.063)	(0.024)	(0.04)

NOTES: The stock variable is the change in the housing stock units at the county level from 1980-2010. Panels A-D refer to different specifications of high versus low growth (at the county level), and whether regulations (at the metro level) are included in the regression. Source: Authors' calculations using housing transactions data, SABINS attendance zone data, local amenities data, and WRI land use regulation data, all described in Section 4.

Table 11: Tickets and Price Appreciation

Property Size	Raw	Components		
(lot percentile)		Ticket	Land	Capital
25^{th}	0.40	0.10	0.02	0.27
50^{th}	0.37	0.08	0.05	0.28
75^{th}	0.37	0.07	0.05	0.27

NOTES: The table reports appreciation rates in total and the percentage points accounted for by each component, using the hedonic pricing model (specification 2 in Tables 5 to 10). The figures are averages across metro areas. The components add up to the first column, subject to rounding.
Source: Authors' calculations using housing transactions data and SABINS attendance zone data described in Section 4.

(subject to rounding error).

In properties of each size, the appreciation in capital price (i.e., the value assigned to square footage, bedrooms, baths, etc.) averages about 27 percent, a majority of the observed price increases, which range from 37 to 40 percent. Most of the remainder occurs in the neighborhood ticket prices, with tickets comprising a larger share of changes in the smaller properties and land values a larger share in larger properties.

Our previous analysis on capitalization emphasized the cross sectional stratification of neighborhoods, but this simple exercise shows that tickets are not fixed anchors immune to cyclical dynamics. This offers another angle by which tickets are important for understanding the housing price function. For instance, ticket appreciation could be relevant for the submarket cyclical dynamics described in Landvoigt et al. (2015).

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 some evidence of both. Importantly, we find empirically that more restrictively regulated cities exhibit more capitalization in ticket prices. Hence, regulation seems to amplify a two-part tariff to the capitalization of local amenities. 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, vice versa, how the effect of zoning depends on amenities). Beyond this basic point, our work has four further implications. First, it lends additional insights into why the semilog hedonic model could be a preferred functional form in empirical work, as well as the limitations of this specification.[27] The concavity of this functional form may help capture the "tilting" induced by tickets. Nevertheless, by forcing capitalization to be proportionate to prices, such hedonic functional forms are misspecified in the presence of tickets. This may bias the hedonic estimates of the willingness to pay for amenities, most certainly so for applications interested in the heterogeneity of willingness to pay by demographic groups consuming different housing bundles. The exercise we report in Table 3 suggests this concern is not just academic.

Second, tickets would have 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 (see, e.g., Banzhaf et al. (2019)). Capitalization into tickets is likely to augment this effect. The increased housing costs enter as a lump sum effect, rather than proportionate to housing, making the gentrification effect even more regressive.

Third, many structural sorting models adopt a discrete-continuous framework in which households first choose a community and then a continuous quantity of housing. At the choice of community, households trade off housing prices against amenities (and, in some applications, wages) (Kuminoff et al. (2013)). Invariably such studies assume housing services are purchased solely on a per-unit basis, without tickets (typically by first estimating a semilog hedonic model to recover community-specific price indices). Our model suggests per-unit housing prices are lower in high-G communities and that the difference in them across communities is lower than often assumed, whereas "virtual income" (income gross

[27] See Kuminoff et al. (2010) for discussion of hedonic specifications.

of ticket payments) is lower in the high-G communities, at least where there are land-use regulations. We conjecture that these adjustments would affect estimates of housing price and income elasticities of demand, as well as have implications for the implied sorting patterns by income and unobserved tastes. Future work might incorporate tickets into a structural model to test this hypothesis, perhaps with simulations as a first step.

Finally, our model and findings have implications for old debates between the "new" and the "benefit" views of the property tax – debates about whether the gross-of-tax price of housing simulates a market for public goods, as Tiebout (1956) envisioned. Previous tests of one model or the other often have conflated questions of *whether* amenities should be capitalized into housing prices with questions as to *how* they should be. We generalize Hamilton's (1975, 1976) models to show that they should be capitalized into ticket prices in the presence of zoning, especially when it constrains the number of lots in an area. In the presence of congested publicly provided goods, efficiency requires pricing access to the goods per se – not just land – to close the commons (Fischel 1985, Banzhaf 2014). In our view, most local public goods and amenities are congestable. Air quality, for example, typically taken for a pure public good, is congestable (hence rivalrous) in the context of community choice, because adding more people into a spatial area likely will reduce local air quality through traffic congestion, etc. Or to put it another way, as more people crowd into an area, maintaining constant air quality may require more expensive formulations of gasoline, more expense on roads to maintain traffic flow, and so forth (Banzhaf (2014)).

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 judgement 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.

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Appendix: Data and Summary Statistics

Table A1: Property Transaction and Attribute Data, by Metro

Metro	Observations		Property Value ($2010)		Property Attributes				
	Trans.	Properties	Deflated	Over Replace	Lot Size	Living Area	Yr. Built	Beds	Baths
					(1000sqf)	(1000sqf)	(yr)	(no.)	(no.)
Akron (OH)	54,110	45,033	130,812	-33,504	26.84	1.93	1962.6	3.10	1.99
Albany (NY)	63,256	54,131	219,654	12,338	54.57	2.25	1960.3	3.47	2.08
Allentown (PA)	49,180	42,507	209,251	17,649	25.46	2.24	1958.6	3.29	2.01
Atlanta (GA)	276,636	217,994	212,372	-15,672	47.23	2.70	1983.0	3.21	2.47
Augusta (GA)	20,698	17,419	156,611	-69,451	96.29	2.42	1979.6	3.15	2.08
Austin (TX)	27,458	26,386	313,200	64,202	24.01	2.49	1984.9		2.28
Bakersfield (CA)	41,298	32,768	168,734	45,503	35.86	1.85	1991.1	3.46	2.13
Baltimore (MD)	190,895	157,883	256,155	104,919	48.79	1.82	1965.4		2.22
Bend (OR)	25,976	20,394	214,536	78,557	40.62	1.95	1989.6	3.11	2.46
Birmingham (AL)	9,803	8,578	185,938	60,401	43.17	1.54	1984.8		1.61
Boston (MA)	191,253	158,879	414,227	224,963	27.46	2.07	1953.3	3.34	1.99
Boulder (CO)	19,860	17,055	435,569	233,883	81.04	2.18	1977.0	3.35	2.68
Bridgeport (CT)	39,443	34,645	625,177	404,755	34.24	2.52	1958.0	3.67	2.38
Buffalo (NY)	81,454	70,227	133,581	-90,784	38.71	2.32	1952.7	3.46	1.87
Charleston (SC)	27,902	23,231	308,342	148,254	23.72	2.02	1981.8	3.24	2.51
Charlotte (NC)	156,644	131,518	213,637	2,577	44.26	2.46	1987.4	3.17	2.44
Chattanooga (TN)	6,607	5,726	229,718	-179,593	232.09	4.06	1976.9	2.80	1.88
Chicago (Cook Co.) (IL)	210,094	168,792	248,824	90,574	6.35	1.95	1950.1		2.02
Chicago (Outside Cook) (IL)	48,682	41,986	280,330	82,357	26.51	2.37	1975.7	3.14	2.43
Chico (CA)	14,501	12,176	208,724		47.34	1.79	1977.5	2.91	2.06
Cincinnati (OH)	130,154	104,785	158,314	-20,036	27.93	2.05	1964.3	3.18	2.19
Cleveland (OH)	161,034	135,728	137,185	-26,278	34.62	1.91	1958.5	3.23	1.97
Colorado Springs (CO)	65,098	53,653	242,221	45,614	46.28	2.17	1982.4	3.30	2.26
Columbia (SC)	15,651	13,074	178,216	-59,755	135.96	2.64	1983.5	3.07	2.10

Table A1: Property Transaction and Attribute Data, by Metro

Metro	Observations		Property Value ($2010)		Property Attributes				
	Trans.	Properties	Deflated	Over Replace	Lot Size	Living Area	Yr. Built	Beds	Baths
Columbus (OH)	110,573	92,238	162,482	-24,968	39.34	2.10	1966.8	3.24	2.13
Corvallis (OR)	5,866	4,992	279,319		29.51	2.12	1976.7	3.21	2.23
Dallas (TX)	25,775	25,259	260,240	8,432	16.59	2.74	1991.1	3.44	2.40
Dayton (OH)	55,588	45,398	110,248	-46,520	34.03	1.90	1960.2	3.09	1.91
Deltona (FL)	49,859	39,976	142,069	24,970	21.07	1.75	1979.9	2.94	1.96
Denver (CO)	233,294	191,255	309,096	119,454	60.44	2.09	1976.7	2.96	2.44
Des Moines (IA)	51,299	42,130	159,348	1,946	30.53	1.78	1973.3	2.90	2.00
Detroit (MI)	169,297	139,560	66,331	-51,210	23.42	1.57	1954.4	3.09	1.60
Dover (DE)	13,801	12,222	203,518	48,018	42.66	1.89	1985.4	3.27	2.45
Durham (NC)	37,556	32,020	260,227	52,246	43.85	2.23	1983.7	3.16	2.40
Eugene (OR)	24,957	20,526	216,042	85,650	25.81	1.59	1975.4	3.09	2.01
Fayetteville (NC)	27,828	23,191	149,204		30.27	1.79	1983.3	3.18	2.27
Fresno (CA)	43,009	35,039	175,298	35,800	41.18	1.97	1970.0	3.11	1.97
Gainesville (FL)	5,456	4,594	294,872		132.35	2.96	1987.4	3.18	2.36
Grand Junction (CO)	18,277	14,270	212,063	63,616	117.90	1.74	1982.2	3.05	1.98
Grand Rapids (MI)	3,889	3,205	99,874	-8,411	156.64	1.43	1966.1	2.94	1.70
Greensboro (NC)	36,599	31,194	176,727	-45,518	51.95	2.49	1979.2	3.12	2.31
Greenville (SC)	50,758	39,601	153,106		32.28	1.84	1983.8	3.06	2.26
Harrisburg (PA)	31,276	26,771	161,939	-8,289	47.34	1.87	1961.2	3.23	1.94
Hartford (CT)	55,893	49,087	265,226	83,632	38.32	2.08	1960.3	3.39	2.02
Huntsville (AL)	1,500	1,353	255,514	30,182	168.66	2.32	1978.9		1.97
Jacksonville (FL)	151,823	122,146	177,458	16,923	23.14	2.16	1984.0	3.22	2.14
Knoxville (TN)	55,398	44,513	177,294	3,296	85.40	1.92	1976.8	2.96	2.15
Lakeland (FL)	83,890	64,435	127,747	-656	19.97	1.83	1986.1	3.25	2.05
Lancaster (PA)	35,134	30,159	194,858	22,037	43.87	1.89	1963.2	3.18	1.97

Table A1: Property Transaction and Attribute Data, by Metro

Metro	Observations		Property Value ($2010)		Property Attributes				
	Trans.	Properties	Deflated	Over Replace	Lot Size	Living Area	Yr. Built	Beds	Baths
Las Vegas (NV)	260,598	205,932	169,415	21,689	6.74	2.19	1991.0	3.23	2.60
Lincoln (NE)	21,363	18,535	157,308	8,368	20.60	1.67	1972.1	2.74	2.24
Little Rock (AR)	35,383	29,555	164,908	-32,618	46.35	2.16	1975.9		1.84
Los Angeles (LA Co.) (CA)	425,071	347,309	501,479	327,751	53.84	2.18	1965.3	3.10	2.25
Los Angeles (Orange Co.) (CA)	54,371	45,625	626,286	449,290	8.84	2.12	1960.3	3.19	2.01
Manchester (NH)	23,192	17,872	243,133	61,327	60.81	2.09	1964.7	3.35	2.03
Medford (OR)	16,844	13,805	208,695	78,854	95.49	1.73	1979.9	2.97	2.00
Memphis (TN)	105,085	82,343	139,056	-39,060	32.62	2.09	1974.3	3.17	2.17
Miami (FL)	422,632	328,959	259,627	106,702	15.01	2.15	1979.9	2.95	2.21
Milwaukee (WI)	50,560	42,286	149,766	-30,496	12.66	2.12	1949.2	3.48	1.82
Minneapolis-St. Paul (MN)	185,337	150,136	239,807	65,347	33.27	2.13	1966.0	3.12	2.07
Mobile (AL)	45	41	173,687	19,950	811.65	1.77	1983.0	3.13	1.77
Myrtle Beach (SC)	13,464	11,205	325,892		290.33	1.90	1982.5	3.02	2.19
Naples (FL)	25,299	19,597	432,890		38.06	2.46	1985.9		
Nashville (TN)	160,748	129,067	210,528	-1,033	103.90	2.37	1982.6	3.08	2.27
New Haven (CT)	40,985	34,917	258,464	76,064	23.81	2.05	1954.1	3.49	2.01
New York City (NY)	271,075	231,590	733,761	485,852	13.52	2.80	1953.4	3.41	2.26
New York City (NJ)	236,466	205,482	429,705	243,116	382.83	2.16	1961.8	1.67	
New London (CT)	13,932	12,306	265,187	105,404	58.29	1.90	1961.5	3.29	1.96
Oklahoma City (OK)	84,521	67,994	173,381	-47,325	26.37	2.29	1974.5	3.03	1.89
Omaha (NE)	61,126	52,468	166,085	2,297	53.00	1.86	1971.3	2.95	2.00
Orlando (FL)	106,787	82,754	203,994	19,646	29.49	2.57	1987.9	3.37	2.59
Ventura (CA)	42,304	35,126	475,694	317,175	14.17	1.95	1973.7	3.23	2.24
Melbourne (FL)	74,346	60,122	143,299	21,398	12.76	1.82	1983.1	3.07	2.06
Panama City (FL)	15,020	12,541	182,093	44,454	69.79	1.84	1981.9	2.84	1.98

Table A1: Property Transaction and Attribute Data, by Metro

Metro	Observations		Property Value ($2010)		Property Attributes				
	Trans.	Properties	Deflated	Over Replace	Lot Size	Living Area	Yr. Built	Beds	Baths
Pensacola (FL)	46,858	39,256	158,354	4,563	40.39	1.96	1983.0	3.22	2.09
Philadelphia (PA)	385,857	329,519	219,386	53,862	61.37	1.93	1958.2	3.16	1.88
Phoenix (AZ)	630,591	471,713	184,295	24,492	10.92	2.28	1987.8		2.42
Pittsburgh (PA)	124,901	109,174	139,806	-23,045	28.71	1.73	1953.7	3.02	1.85
Portland (OR)	146,556	122,196	274,842	115,678	41.33	1.91	1974.2	3.10	2.30
Poughkeepsie (NY)	32,125	28,409	286,728	103,866	78.12	2.16	1965.2	3.34	2.26
Providence (RI)	85,610	67,226	239,388	68,764	24.45	1.98	1954.2	3.52	1.95
Raleigh (NC)	115,187	97,893	240,015	17,331	31.95	2.47	1990.2	0.84	2.73
Reno (NV)	41,780	34,663	245,051	84,714	24.40	2.27	1987.0	3.28	2.47
Richmond (VA)	71,617	59,184	241,156	54,056	100.38	2.23	1984.1	3.48	2.65
Riverside-San Bern. (CA)	419,718	329,222	222,813	78,312	15.42	2.03	1984.0	3.28	2.38
Rochester (NY)	28,849	27,315	131,861	-56,644	46.59	1.99	1957.7	3.20	1.99
Sacramento (CA)	134,378	108,278	232,548	102,835	92.54	1.77	1979.0	3.31	2.13
St. Louis (MO)	154,688	126,060	170,322	10,634	17.67	1.85	1963.1	2.88	1.95
Salem (OR)	29,417	24,217	199,693	42,782	38.63	1.86	1976.8	3.15	2.01
San Diego (CA)	70,797	59,915	524,606	342,895	50.76	2.15	1965.0	3.17	2.08
San Francisco-Oakland (CA)	203,276	169,784	575,233	390,867	21.22	2.24	1965.5	3.27	2.15
San Jose (CA)	82,852	69,802	634,937	464,604	8.46	2.02	1971.3	3.08	2.10
Seattle (WA)	245,008	212,611	375,461	199,708	47.54	2.09	1977.3	3.06	2.24
Springfield (MA)	37,952	30,591	190,882		43.88	1.98	1953.2	3.45	1.80
Stockton (CA)	57,706	45,813	185,836	53,938	13.44	1.90	1982.9	3.47	2.39
Tampa-St. Pete. (FL)	279,884	221,841	173,502	24,155	47.01	2.04	1977.7	3.16	2.07
Toledo (OH)	39,387	32,416	102,237	-66,529	25.22	1.98	1953.9	3.09	1.75
Tucson (AZ)	42,693	34,381	221,468	43,193	20.48	2.37	1992.0		2.02
Tulsa (OK)	65,146	52,842	173,229	-47,549	36.00	2.31	1973.2	2.89	2.04

Table A1: Property Transaction and Attribute Data, by Metro

Metro	Observations		Property Value ($2010)		Property Attributes				
	Trans.	Properties	Deflated	Over Replace	Lot Size	Living Area	Yr. Built	Beds	Baths
Norfolk (VA)	43,425	35,864	244,808	84,681	22.49	1.87	1975.2	3.26	2.43
Washington (DC)	409,791	330,986	420,382	238,262	25.72	2.14	1978.1	3.37	2.95
Wilmington (NC)	22,548	19,152	260,562	71,628	44.84	2.18	1984.6	3.08	2.36
Winston (NC)	35,173	30,148	169,735	-32,707	36.79	2.25	1980.7	3.07	2.33
Worcester (MA)	43,257	34,439	252,499	70,111	50.07	2.06	1959.0	3.44	1.96

Source: Authors' calculations using local amenities and land use regulation data as described in Section 4.

Table A2: Variance Decomposition Analysis of Housing Stock Attributes

	1 Lot Size	2 Living Area	3 Year Built	4 Share Built Since 2000	5 Share Built Since 1960
Share of Within-Neighborhood Variance					
Mean	0.792	0.819	0.692	0.829	0.718
Std Dev	0.155	0.130	0.184	0.138	0.186
Place-Level Regressions					
Reg Index	-0.019	-0.015	-0.015	-0.017	-0.014
	(0.005)	(0.004)	(0.006)	(0.004)	(0.006)
MLS Index	-0.010	0.006	0.002	0.003	0.012
	(0.012)	(0.010)	(0.015)	(0.012)	(0.015)
Cons	0.806	0.819	0.694	0.831	0.712
	(0.011)	(0.009)	(0.013)	(0.010)	(0.014)
R^2	0.0133	0.0123	0.0057	0.0123	0.0052
J	958	958	983	896	957

NOTES: The outcome variable is the share of variance in the housing stock attribute within a Census Place (i.e. municipality) that can be attributed to block group effects. To be included in the regression, there needs to be available land use regulation index (WRI) and property attribute information, and the property attribute must contain variance both within and between block group level. Standard errors in parentheses. Source: Authors' calculations using housing transactions data as described in Section 4.

Table A3: Summary Statistics for Second Stage Model

Metro				Neighborhood Attributes				
	WRI	Munis w/. WRI	Neighbor-hoods	Test Score: Math (w/i. state Z)	Dist to CBD (miles)	CERCLA Sites (no. w/i. 3km)	Ozone (days vio.)	Crime Rate (ann. per 10k)
Akron (OH)	0.52	11	88	-0.13	7.85	0.01	0.00	3,313.88
Albany (NY)	0.30	6	128	0.17	14.56	0.07	0.39	3,216.14
Allentown (PA)	0.42	8	89	0.32	12.72	0.12	0.12	2,739.84
Atlanta (GA)	0.15	30	596	0.25	21.43	0.00	3.23	5,369.10
Augusta (GA)	-1.42	4	77	-0.20	11.14	0.11	0.00	4,134.48
Austin (TX)	0.36	5	194	0.46	12.35	0.00	2.06	3,328.32
Bakersfield (CA)	0.96	4	126	-0.01	15.85	0.02	36.62	3,748.67
Baltimore (MD)	2.32	8	380	0.24	12.13	0.05	0.96	5,090.14
Bend (OR)	1.59	2	21	0.73	10.33	0.00	0.43	4,334.47
Birmingham (AL)	-0.64	4	24	0.44	21.83	0.01	1.06	3,109.10
Boston (MA)	2.47	16	603	0.02	17.42	0.10	1.51	2,307.68
Boulder (CO)	5.32	4	42	0.56	9.57	0.01	2.71	2,306.78
Bridgeport (CT)	0.16	4	141	0.19	7.61	0.07	2.04	2,003.91
Buffalo (NY)	-0.26	8	132	-0.04	11.30	0.03	1.00	3,228.43
Charleston (SC)	-1.09	5	52	0.27	12.60	0.09	0.00	3,883.73
Charlotte (NC)	-0.50	8	169	0.19	13.59	0.05	1.66	3,544.87
Chattanooga (TN)	-1.14	1	53	0.43	10.50	0.04	1.27	5,959.70
Chicago (Cook Co.) (IL)	-0.04	46	772	0.04	12.77	0.00	0.09	3,019.74
Chicago (Outside Cook) (IL)	0.65	55	221	0.46	37.19	0.13	0.65	2,206.82
Chico (CA)	2.05	4	32	-0.28	15.70	0.04	5.66	4,746.70
Cincinnati (OH)	-0.78	25	216	0.19	14.09	0.07	1.74	4,322.80
Cleveland (OH)	-0.06	32	271	-0.25	14.53	0.00	0.57	2,556.28
Colorado Springs (CO)	1.07	3	114	0.61	8.98	0.00	0.25	3,957.01
Columbia (SC)	-1.07	5	83	0.34	10.55	0.03	0.00	5,863.58

Table A3: Summary Statistics for Second Stage Model

Metro				Neighborhood Attributes				
	WRI	Munis w/. WRI	Neighbor-hoods	Test Score: Math (w/i. state Z)	Dist to CBD (miles)	CERCLA Sites (no. w/i. 3km)	Ozone (days vio.)	Crime Rate (ann. per 10k)
Columbus (OH)	0.18	10	258	-0.02	13.16	0.00	0.28	3,577.70
Corvallis (OR)	0.42	3	12	0.78	6.83	0.01	0.55	2,904.40
Dallas (TX)	-0.33	45	153	0.69	20.82	0.00	11.10	2,611.24
Dayton (OH)	-0.65	10	102	-0.18	7.58	0.18	1.16	3,740.26
Deltona (FL)	1.14	7	45	0.35	14.51	0.01	0.00	5,611.76
Denver (CO)	1.62	13	398	0.34	11.93	0.07	1.27	3,831.78
Des Moines (IA)	-1.16	8	84	-0.11	8.11	0.12	0.00	2,887.08
Detroit (MI)	0.41	25	419	0.49	16.53	0.04	0.73	3,520.56
Dover (DE)	1.79	4	20	0.54	8.10	0.24	0.26	5,765.25
Durham (NC)	1.40	5	57	0.05	13.29	0.00	0.00	4,423.26
Eugene (OR)	1.03	2	59	0.49	10.19	0.00	0.09	4,665.00
Fayetteville (NC)	-0.65	3	47	-0.09	6.87	0.08	0.58	6,984.73
Fresno (CA)	2.16	6	162	0.25	9.65	0.10	41.53	4,849.83
Gainesville (FL)	0.52	2	24	0.36	8.60	0.17	0.00	5,723.45
Grand Junction (CO)	1.16	3	24	0.41	7.13	0.00	0.02	3,481.38
Grand Rapids (MI)	0.30	2	13	0.74	31.90	0.00	1.07	3,851.89
Greensboro (NC)	-0.56	8	101	0.13	10.67	0.00	0.18	5,423.14
Greenville (SC)	-1.26	5	65	0.68	10.17	0.12	0.00	4,821.22
Harrisburg (PA)	0.95	6	74	0.12	10.54	0.05	0.02	2,693.54
Hartford (CT)	0.59	3	165	0.26	11.51	0.07	1.40	2,480.12
Huntsville (AL)	-1.91	3	21	0.52	10.43	0.00	0.63	4,390.12
Jacksonville (FL)	0.15	4	150	0.34	12.74	0.11	0.43	5,270.20
Knoxville (TN)	-0.15	3	69	0.27	11.05	0.02	1.09	6,290.56
Lakeland (FL)	0.79	5	64	0.14	12.91	0.04	0.01	5,969.47

Table A3: Summary Statistics for Second Stage Model

Metro				Neighborhood Attributes				
	WRI	Munis w/. WRI	Neighbor-hoods	Test Score: Math (w/i. state Z)	Dist to CBD (miles)	CERCLA Sites (no. w/i. 3km)	Ozone (days vio.)	Crime Rate (ann. per 10k)
Lancaster (PA)	0.77	8	71	0.32	8.64	0.05	0.72	2,623.20
Las Vegas (NV)	-1.30	4	190	0.09	9.84	0.00	0.75	2,810.88
Lincoln (NE)	-0.52	2	45	0.70	4.81	0.00	0.00	4,152.44
Little Rock (AR)	-1.19	7	97	0.06	13.17	0.02	1.35	6,104.04
Los Angeles (LA Co.) (CA)	1.18	36	1,142	0.37	15.35	0.16	11.61	2,919.73
Los Angeles (Orange Co.) (CA)	0.95	15	348	0.70	29.99	0.02	3.03	2,289.83
Manchester (NH)	2.47	2	58	0.42	12.26	0.09	0.08	2,403.00
Medford (OR)	1.94	2	32	0.19	8.66	0.00	0.00	3,832.89
Memphis (TN)	1.36	3	147	-0.45	11.39	0.08	0.77	4,781.82
Miami (FL)	1.29	36	437	0.36	16.67	0.16	0.30	4,971.97
Milwaukee (WI)	0.81	8	143	-0.71	8.92	0.05	1.06	3,786.60
Minneapolis-St. Paul (MN)	0.75	67	313	0.78	15.92	0.12	0.00	5,230.23
Myrtle Beach (SC)	-1.55	3	22	0.75	15.90	0.00	0.11	11,996.11
Naples (FL)	1.07	2	29	0.20	17.81	0.00	0.00	3,182.22
Nashville (TN)	-0.77	9	207	0.35	20.04	0.00	0.28	3,934.06
New Haven (CT)	-0.04	5	148	0.01	9.64	0.11	0.77	3,325.77
New York City (NY)	1.12	23	906	0.19	15.77	0.19	1.18	1,836.21
New York City (NJ)	1.61	42	807	0.29	23.26	0.32	1.29	1,996.85
New London (CT)	0.32	3	51	0.13	9.25	0.03	0.79	2,666.77
Oklahoma City (OK)	-0.78	13	166	0.16	9.90	0.01	1.38	4,665.56
Omaha (NE)	-1.14	4	179	0.32	9.88	0.04	0.00	3,606.82
Orlando (FL)	0.73	10	166	0.39	13.36	0.06	0.11	4,100.49
Ventura (CA)	2.59	8	127	0.40	12.14	0.08	7.00	2,003.29
Melbourne (FL)	0.95	7	53	0.64	20.21	0.04	0.00	5,080.84

Table A3: Summary Statistics for Second Stage Model

Metro				Neighborhood Attributes				
	WRI	Munis w/. WRI	Neighbor-hoods	Test Score: Math (w/i. state Z)	Dist to CBD (miles)	CERCLA Sites (no. w/i. 3km)	Ozone (days vio.)	Crime Rate (ann. per 10k)
Panama City (FL)		2	19	0.35	14.48	0.00	0.82	6,331.26
Pensacola (FL)	-1.16	2	46	0.34	11.00	0.20	1.33	5,113.35
Philadelphia (PA)	1.59	28	747	0.10	16.46	0.27	0.60	3,301.91
Phoenix (AZ)	1.33	16	533	0.34	17.10	0.02	0.54	4,142.59
Pittsburgh (PA)	0.25	25	227	0.46	13.67	0.03	0.54	2,135.89
Portland (OR)	0.99	22	328	0.46	12.57	0.10	0.80	3,238.51
Poughkeepsie (NY)	0.53	4	90	0.16	17.58	0.11	0.82	3,048.94
Providence (RI)	2.48	7	236	0.10	13.00	0.20	0.89	2,676.87
Raleigh (NC)	1.03	6	131	0.45	12.09	0.03	0.00	3,568.69
Reno (NV)	0.08	3	65	0.47	6.95	0.00	0.00	3,396.00
Richmond (VA)	-0.37	1	103	0.47	11.96	0.07	0.00	5,002.58
Riverside-San Bern. (CA)	1.03	22	566	0.31	21.93	0.05	41.97	3,194.86
Rochester (NY)	-0.40	6	71	0.44	11.30	0.00	0.10	3,281.72
Sacramento (CA)	1.03	6	266	0.45	16.44	0.05	13.09	3,364.52
St. Louis (MO)	-1.05	27	308	-0.03	16.91	0.05	0.85	4,066.41
Salem (OR)	1.04	3	72	0.33	8.52	0.00	1.02	3,283.28
San Diego (CA)	1.33	11	353	0.55	16.08	0.00	1.51	2,745.82
San Francisco-Oakland (CA)	1.57	25	539	0.57	14.02	0.03	0.87	3,125.13
San Jose (CA)	0.73	4	219	0.77	7.89	0.73	1.40	2,549.74
Seattle (WA)	2.05	27	522	0.51	20.26	0.12	0.70	4,593.14
Springfield (MA)	0.99	5	125	-0.54	12.84	0.00	3.08	3,484.53
Stockton (CA)	1.35	4	102	-0.13	10.60	0.08	4.49	4,046.12
Tampa-St. Pete. (FL)	-0.05	10	247	0.26	16.09	0.08	0.29	4,964.67
Toledo (OH)	-0.91	8	98	0.03	8.75	0.00	0.23	2,918.87

Table A3: Summary Statistics for Second Stage Model

Metro				Neighborhood Attributes				
	WRI	Munis w/. WRI	Neighbor-hoods	Test Score: Math (w/i. state Z)	Dist to CBD (miles)	CERCLA Sites (no. w/i. 3km)	Ozone (days vio.)	Crime Rate (ann. per 10k)
Tucson (AZ)	2.13	5	126	0.24	9.15	0.00	0.05	3,350.48
Tulsa (OK)	-1.29	8	118	-0.01	10.08	0.01	1.85	3,841.45
Norfolk (VA)	0.28	6	77	0.14	10.83	0.05	0.00	4,229.31
Washington (DC)	0.77	15	721	0.20	18.29	0.04	0.68	3,950.20
Wilmington (NC)	-1.02	5	38	0.33	13.08	0.02	0.11	6,018.12
Winston (NC)	-1.26	3	54	0.30	9.87	0.01	0.38	5,769.61
Worcester (MA)	3.49	1	103	-0.25	11.60	0.01	2.95	2,517.76
Mean	0.49	11	198	0.27	13.26	0.06	2.34	3,938.00
SD	1.22	12	217	0.29	5.17	0.09	6.93	1,423.53

Source: Authors' calculations using local amenities and land use regulation data as described in Section 4.

Table A4: Estimation of the Housing Services Function

Model	4	5	6
Specification			
lot size	ln	ln	ln
sqft	ln		
Bedrooms		dummies	
Baths		dummies	dummies
Vintage		dummies	dummies
Interactions	ln(lot size) X ln(sqft)	ln(lot size) X I(many beds); I(many baths) X I(many beds)	vintage dummies X ln(sqft)
Parameters	3	26	25
Estimation			
MSE criterion	2.14	2.52	2.02
R^2	0.91	0.89	0.91
Function: $\hat{h}$			
Mean	3.79	2.72	30.61
SD	38.35	30.98	41.10
Correlations			
4	1.00	0.68	0.97
5	0.68	1.00	0.77
6	0.97	0.77	1.00
α_n Parameters (Initial Stage)			
Mean	127.34	206.27	139.94
SD	107.75	150.55	115.60
Correlations			
4	1.00	0.86	0.99
5	0.86	1.00	0.90
6	0.99	0.90	1.00
β_n Parameters (Initial Stage)			
Mean	2.39	2.97	2.39
SD	1.50	2.19	1.45
Correlations			
4	1.00	0.69	0.94
5	0.69	1.00	0.74
6	0.94	0.74	1.00

NOTES: Column numbers refer to the model specifications as denoted in Tables 4 to 10. Source: Authors' calculations using housing transactions data as described in Section 4.

Table A5: Mean Estimated Ticket and Slope Parameters, by Metro

Metro	Coef. Type	Land	Replace Cost	Hedonic	Estimated Services:		
					Land, Area	Land, Rooms	4 + Vintage, Bath
Akron (OH)	α	117,935.7	7,190.6	-13,413.3	136,971.4	263,671.9	158,042.9
Akron (OH)	β	4,871.3	-6,126.5	927.4	1,203.3	1,928.1	1,159.9
Albany (NY)	α	275,133.6	141,872.6	101,346.2	276,590.6	415,704.4	311,960.7
Albany (NY)	β	6,202.2	-11,963.2	492.3	1,074.8	2,630.5	755.7
Allentown (PA)	α	233,025.2	67,988.1	47,214.5	247,093.6	429,413.2	272,421.3
Allentown (PA)	β	8,142.0	-6,704.3	53.2	1,170.2	2,868.0	1,059.4
Atlanta (GA)	α	196,961.8	40,505.4	-38,537.9	249,445.6	308,121.5	298,618.7
Atlanta (GA)	β	8,729.0	-4,813.2	3,242.1	1,064.4	2,973.8	784.9
Augusta (GA)	α	132,266.6	-7,792.7	-36,476.2	144,309.5	219,177.4	160,488.0
Augusta (GA)	β	3,804.1	-3,451.4	1,648.6	1,667.6	2,516.9	1,784.8
Austin (TX)	α	259,726.8	54,581.5	105,446.1	352,832.7	495,043.0	426,853.3
Austin (TX)	β	14,315.9	1,904.5	-3,341.6	1,219.5	5,107.7	886.4
Bakersfield (CA)	α	263,476.8	59,860.0	46,734.4	175,123.6	294,195.6	209,800.9
Bakersfield (CA)	β	3,780.8	1,457.9	1,898.2	2,126.1	2,464.2	1,689.1
Baltimore (MD)	α	382,452.2	198,069.7	172,348.3	338,555.2	584,827.1	385,252.0
Baltimore (MD)	β	9,788.2	-4,204.6	2,310.3	2,876.1	3,607.5	2,928.8
Bend (OR)	α	315,514.4	111,695.0	254,430.2	219,233.0	333,141.4	250,955.6
Bend (OR)	β	3,050.4	1,056.8	1,902.9	2,610.8	3,197.2	2,047.2
Birmingham (AL)	α	285,176.0	94,110.1	-104,530.5	233,594.2	327,580.0	257,240.1
Birmingham (AL)	β	1,920.8	645.0	774.5	1,987.7	2,886.4	1,776.6
Boston (MA)	α	467,978.5	238,891.0	-13,121.3	538,221.0	1,118,942.0	616,256.1
Boston (MA)	β	45,475.0	32,042.0	25,275.3	4,961.8	7,813.6	6,148.9
Boulder (CO)	α	602,671.2	428,110.1	243,540.0	483,656.9	753,693.1	537,887.0
Boulder (CO)	β	10,092.5	1,276.9	2,662.2	4,782.4	5,032.9	4,233.8
Bridgeport (CT)	α	743,065.2	516,993.6	-6,698.5	596,769.0	925,601.4	661,867.7

Table A5: Mean Estimated Ticket and Slope Parameters, by Metro

Metro	Coef. Type	Land	Replace Cost	Hedonic	Estimated Services:		
					Land, Area	Land, Rooms	4 + Vintage, Bath
Bridgeport (CT)	β	11,061.7	3,932.8	-3,118.0	3,535.7	6,745.1	4,076.3
Buffalo (NY)	α	152,678.8	36,546.3	78,430.2	150,767.9	311,433.3	160,425.5
Buffalo (NY)	β	5,829.2	-15,440.0	-1,023.2	1,107.1	2,460.7	1,417.3
Charleston (SC)	α	440,993.6	201,554.4	204,074.2	198,604.0	505,871.7	281,138.3
Charleston (SC)	β	6,687.1	4,028.7	3,980.3	4,835.8	4,851.2	4,020.6
Charlotte (NC)	α	358,057.0	-24,171.8	-214,378.0	255,840.4	293,305.6	292,778.6
Charlotte (NC)	β	1,169.7	1,641.6	1,308.9	879.6	2,533.2	585.7
Chattanooga (TN)	α	203,671.6	-1,683.8	122,211.3	140,030.1	85,384.7	119,051.8
Chattanooga (TN)	β	2,080.1	-2,552.1	1,029.9	1,407.6	3,641.5	1,668.4
Chicago (Cook Co.) (IL)	α	267,488.2	201,783.6	100,079.4	364,493.3	616,453.0	391,418.7
Chicago (Cook Co.) (IL)	β	19,829.9	-5,055.6	-2,763.8	1,318.0	3,546.8	1,360.2
Chicago (Outside Cook) (IL)	α	368,941.3	133,352.8	131,464.1	261,665.6	428,767.8	303,970.7
Chicago (Outside Cook) (IL)	β	5,286.2	1,369.7	2,126.4	2,489.7	3,453.0	2,140.0
Chico (CA)	α	304,821.3		77,636.4	266,047.8	416,860.5	289,659.8
Chico (CA)	β	4,127.0		1,869.3	2,393.3	2,728.2	2,365.6
Cincinnati (OH)	α	186,906.2	-6,182.2	36,751.4	140,705.3	282,406.2	164,821.8
Cincinnati (OH)	β	4,883.1	-2,877.2	2,706.0	1,914.4	2,448.8	1,963.5
Cleveland (OH)	α	194,455.1	-794.5	3,620.1	167,076.5	269,684.5	181,192.4
Cleveland (OH)	β	3,670.1	-2,921.7	-1,042.6	819.3	1,866.6	1,005.3
Colorado Springs (CO)	α	256,520.0	219,712.2	47,777.5	310,632.5	448,821.7	341,986.9
Colorado Springs (CO)	β	10,778.8	-7,522.0	3,964.2	1,956.7	3,382.2	1,749.7
Columbia (SC)	α	191,955.2	8,899.0	83,168.4	210,076.0	221,123.5	214,328.7
Columbia (SC)	β	1,873.5	-1,687.2	706.2	662.1	2,720.0	702.6
Columbus (OH)	α	179,665.4	54,292.2	22,580.8	172,003.9	311,654.7	204,196.2
Columbus (OH)	β	6,920.3	-5,333.9	2,411.2	1,486.7	2,599.3	1,368.9

Table A5: Mean Estimated Ticket and Slope Parameters, by Metro

Metro	Coef. Type	Land	Replace Cost	Hedonic	Estimated Services:		
					Land, Area	Land, Rooms	4 + Vintage, Bath
Corvallis (OR)	α	423,579.7		203,446.2	340,488.8	547,943.2	364,675.2
Corvallis (OR)	β	4,932.3		2,476.7	2,571.1	3,793.4	2,730.7
Dallas (TX)	α	211,185.2	-40,767.8	-76,152.9	391,802.4	366,851.5	505,698.1
Dallas (TX)	β	11,857.8	1,385.3	4,321.1	-688.7	2,765.4	-1,839.1
Dayton (OH)	α	128,755.3	-5,773.7	15,851.4	124,323.4	242,733.7	139,090.6
Dayton (OH)	β	3,854.6	-6,156.5	254.4	1,042.8	1,854.0	1,119.7
Deltona (FL)	α	137,442.8	17,354.2	-46,881.4	151,857.5	277,231.4	160,872.6
Deltona (FL)	β	5,762.9	1,283.5	2,177.0	1,997.8	2,741.8	2,084.0
Denver (CO)	α	237,802.5	200,628.7	596,225.2	366,364.0	645,320.8	420,992.2
Denver (CO)	β	23,324.1	1,747.6	6,205.3	2,295.3	3,944.8	2,029.3
Des Moines (IA)	α	181,068.6	121,526.2	101,728.3	214,208.3	321,134.0	234,843.8
Des Moines (IA)	β	5,610.3	-5,090.4	2,452.8	1,327.1	2,300.7	1,143.9
Detroit (MI)	α	83,034.1	22,332.3	53,410.8	96,283.0	137,832.5	103,062.5
Detroit (MI)	β	3,360.7	-10,966.0	2,450.6	762.9	1,328.1	962.5
Dover (DE)	α	360,992.4	65,104.8	41,652.0	238,191.2	350,444.0	257,729.4
Dover (DE)	β	1,050.1	627.2	932.9	2,148.5	1,724.2	1,821.2
Durham (NC)	α	159,728.5	-7,865.7	-150,100.0	280,425.7	354,237.6	328,951.0
Durham (NC)	β	9,596.0	2,833.7	2,119.8	1,798.0	3,063.8	1,507.5
Eugene (OR)	α	358,652.0	131,574.8	92,683.5	299,465.3	445,038.0	326,551.0
Eugene (OR)	β	2,997.7	1,508.9	2,191.8	2,478.9	2,178.7	2,322.2
Fayetteville (NC)	α	197,134.1		-53,218.4	141,646.6	258,114.0	172,747.4
Fayetteville (NC)	β	3,246.3		2,181.3	2,316.5	2,336.7	2,037.6
Fresno (CA)	α	188,496.4	99,014.4	63,969.0	195,825.1	386,019.7	223,484.6
Fresno (CA)	β	7,621.4	-1,722.0	4,260.9	2,265.4	3,330.2	2,401.6
Gainesville (FL)	α	486,137.4		69,070.7	292,098.0	289,602.9	287,775.4

Table A5: Mean Estimated Ticket and Slope Parameters, by Metro

Metro	Coef. Type	Land	Replace Cost	Hedonic	Estimated Services:		
					Land, Area	Land, Rooms	4 + Vintage, Bath
Gainesville (FL)	β	955.0		657.2	251.8	2,612.6	476.6
Grand Junction (CO)	α	330,895.3	114,360.9	1,868.5	278,082.9	351,733.2	287,673.8
Grand Junction (CO)	β	1,589.9	136.8	1,183.2	1,906.2	2,216.7	1,877.5
Grand Rapids (MI)	α	173,573.4	-7,330.6	141,400.1	155,138.6	171,842.2	159,101.7
Grand Rapids (MI)	β	214.0	-186.0	-102.2	802.2	588.0	817.0
Greensboro (NC)	α	185,606.3	91,631.1	80,719.7	145,051.7	258,023.3	178,422.8
Greensboro (NC)	β	4,065.9	-5,026.7	1,549.5	2,048.4	2,393.1	1,627.5
Greenville (SC)	α	272,045.8		-8,954.9	157,116.0	299,906.5	189,797.6
Greenville (SC)	β	1,167.6		469.5	2,256.0	1,600.0	1,838.6
Harrisburg (PA)	α	202,932.2	-36,492.6	28,440.1	194,473.2	324,042.6	210,761.9
Harrisburg (PA)	β	5,889.6	-2,880.7	1,711.0	1,548.9	2,514.3	1,779.8
Hartford (CT)	α	336,029.9	148,442.2	145,243.8	300,944.1	489,947.6	317,158.8
Hartford (CT)	β	4,770.6	171.7	1,049.4	2,222.5	3,812.2	2,559.3
Huntsville (AL)	α	34,457.8	-154,177.8	-126,699.5	237,151.8	100,102.0	249,445.4
Huntsville (AL)	β	4,194.2	1,999.7	1,818.8	524.4	3,982.5	524.3
Jacksonville (FL)	α	199,032.5	56,059.7	26,997.4	147,491.6	283,433.2	186,125.2
Jacksonville (FL)	β	6,364.3	-1,616.1	1,684.1	2,080.8	2,844.7	1,716.9
Knoxville (TN)	α	254,094.8	41,473.4	-128,961.7	166,935.2	282,546.5	184,318.4
Knoxville (TN)	β	2,330.0	-953.6	1,117.5	2,194.6	2,947.3	2,003.4
Lakeland (FL)	α	189,431.1	9,799.2	-32,664.8	122,495.1	224,985.4	144,066.9
Lakeland (FL)	β	2,235.5	-360.4	899.5	1,948.8	1,678.8	1,712.1
Lancaster (PA)	α	236,804.0	18,827.9	81,019.1	217,856.5	400,929.4	244,665.8
Lancaster (PA)	β	6,698.3	615.2	3,570.4	1,897.9	2,830.0	2,186.3
Las Vegas (NV)	α	66,790.9	-8,196.8	-196,727.5	137,246.1	313,724.1	191,261.4
Las Vegas (NV)	β	20,721.3	4,982.5	14,975.1	2,443.3	3,678.2	1,628.6

Table A5: Mean Estimated Ticket and Slope Parameters, by Metro

Metro	Coef. Type	Land	Replace Cost	Hedonic	Estimated Services:		
					Land, Area	Land, Rooms	4 + Vintage, Bath
Lincoln (NE)	α	163,129.4	88,768.8	89,872.0	203,236.8	333,165.2	226,510.8
Lincoln (NE)	β	8,062.3	-4,010.5	1,491.0	2,008.3	2,586.7	1,785.5
Little Rock (AR)	α	161,316.7	112,029.6	48,893.2	154,802.6	349,295.1	181,893.9
Little Rock (AR)	β	6,371.8	-7,169.7	1,935.4	1,566.0	3,952.9	1,660.9
Los Angeles (LA Co.) (CA)	α	828,591.9	621,569.3	194,495.9	651,136.8	949,602.9	710,236.3
Los Angeles (LA Co.) (CA)	β	9,802.7	2,498.5	1,188.2	2,633.7	5,256.5	2,625.3
Los Angeles (Orange Co.) (CA)	α	614,881.7	603,950.2	485,487.2	842,985.2	1,542,386.0	910,575.9
Los Angeles (Orange Co.) (CA)	β	40,968.3	20,620.7	20,588.3	5,016.2	10,190.4	6,726.4
Manchester (NH)	α	338,310.2	108,955.2	135,653.3	315,512.8	456,081.4	331,666.7
Manchester (NH)	β	3,664.5	19.7	1,102.6	1,776.1	3,102.2	1,969.5
Medford (OR)	α	339,415.2	114,640.4	27,464.8	252,483.2	422,305.2	283,346.2
Medford (OR)	β	2,285.2	1,164.5	1,444.5	2,407.6	2,534.9	2,238.7
Memphis (TN)	α	161,186.1	-24,361.6	70,559.3	116,155.5	248,728.2	151,471.3
Memphis (TN)	β	4,079.3	-2,455.8	1,003.4	1,226.2	2,375.0	1,214.3
Miami (FL)	α	251,904.6	146,967.7	-138,727.2	215,492.4	459,083.2	284,530.6
Miami (FL)	β	12,499.2	2,638.2	4,233.4	2,872.0	4,248.7	2,452.3
Milwaukee (WI)	α	119,189.7	124,769.6	43,391.1	218,716.4	397,690.2	226,592.9
Milwaukee (WI)	β	12,673.0	-13,857.0	1,801.7	526.5	2,970.1	746.2
Minneapolis-St. Paul (MN)	α	290,340.2	132,649.6	91,849.0	334,310.7	486,237.7	359,867.3
Minneapolis-St. Paul (MN)	β	8,368.1	-139.5	4,884.2	1,984.0	3,411.8	2,369.0
Myrtle Beach (SC)	α	205,183.8		-779,988.4	-125,925.2	775,316.5	69,492.3
Myrtle Beach (SC)	β	12,350.1		5,562.8	12,162.7	13,541.0	10,016.5
Naples (FL)	α	439,826.8		1,019,844.0	155,928.8	318,547.4	272,276.4
Naples (FL)	β	10,901.6		6,842.2	5,557.5	16,889.7	4,807.0
Nashville (TN)	α	259,856.5	106,287.7	17,778.7	193,462.1	305,287.4	229,768.5

Table A5: Mean Estimated Ticket and Slope Parameters, by Metro

Metro	Coef. Type	Land	Replace Cost	Hedonic	Estimated Services:		
					Land, Area	Land, Rooms	4 + Vintage, Bath
Nashville (TN)	β	3,431.4	-3,074.7	970.0	1,644.0	2,711.6	1,333.4
New Haven (CT)	α	371,016.6	155,649.2	106,772.1	344,437.0	517,050.4	362,653.8
New Haven (CT)	β	5,002.3	-879.5	582.8	1,771.6	3,258.8	2,057.7
New York City (NY)	α	616,489.9	499,538.0	633,136.7	1,440,318.0	1,757,097.0	1,284,200.0
New York City (NY)	β	56,239.5	15,108.0	-6,640.0	-8,532.6	10,502.2	-7,249.5
New York City (NJ)	α	591,180.2	387,861.3	362,994.0	497,200.6	741,555.7	570,232.8
New York City (NJ)	β	10,939.6	2,128.1	5,251.9	3,868.4	6,791.0	4,333.2
New London (CT)	α	391,089.3	189,290.6	132,666.9	350,599.9	483,818.2	370,069.0
New London (CT)	β	3,180.5	129.2	1,257.6	2,065.9	2,719.3	2,138.9
Oklahoma City (OK)	α	71,787.7	68,202.1	-4,936.8	150,829.3	344,227.7	206,284.1
Oklahoma City (OK)	β	11,150.2	-6,865.6	4,600.2	1,053.9	3,781.4	601.9
Omaha (NE)	α	131,477.9	87,134.3	70,524.8	189,678.5	326,861.4	222,399.2
Omaha (NE)	β	9,177.8	-4,595.8	5,055.3	1,793.5	2,716.9	1,478.6
Orlando (FL)	α	205,718.6	40,036.1	-273,154.2	203,815.8	297,160.6	230,947.5
Orlando (FL)	β	7,503.6	1,620.5	3,380.3	1,531.1	2,570.5	1,293.6
Ventura (CA)	α	703,651.8	520,630.2	188,489.8	571,966.6	1,016,554.0	675,131.2
Ventura (CA)	β	14,388.8	6,332.5	14.9	5,239.5	6,391.1	4,806.1
Melbourne (FL)	α	144,342.5	44,608.2	-40,511.9	144,488.0	270,952.8	169,250.7
Melbourne (FL)	β	7,200.2	-224.6	3,801.6	2,329.5	2,623.9	2,090.5
Pensacola (FL)	α	206,016.4	-60,291.3	17,333.5	147,311.9	256,345.0	165,072.5
Pensacola (FL)	β	2,859.1	2,122.2	1,448.7	2,222.9	2,738.3	2,127.7
Philadelphia (PA)	α	290,170.3	112,849.2	42,062.1	303,761.4	465,525.8	343,739.7
Philadelphia (PA)	β	12,493.1	-6,779.4	6,055.6	1,717.3	2,819.8	2,104.7
Phoenix (AZ)	α	155,961.2	21,885.2	-98,054.7	205,245.8	311,999.3	250,790.1
Phoenix (AZ)	β	12,293.7	1,149.3	7,544.9	1,491.3	4,261.8	872.6

Table A5: Mean Estimated Ticket and Slope Parameters, by Metro

Metro	Coef. Type	Land	Replace Cost	Hedonic	Estimated Services:		
					Land, Area	Land, Rooms	4 + Vintage, Bath
Pittsburgh (PA)	α	207,736.8	-59,465.8	14,607.3	150,726.6	324,101.0	174,852.3
Pittsburgh (PA)	β	3,746.7	90.3	1,553.4	1,802.8	2,258.7	2,007.5
Portland (OR)	α	378,454.0	227,245.8	83,672.9	369,763.7	539,539.1	401,073.2
Portland (OR)	β	9,132.3	-812.8	114.6	2,325.9	3,531.6	2,359.3
Poughkeepsie (NY)	α	377,795.2	192,273.4	82,328.4	387,404.3	478,278.1	404,975.4
Poughkeepsie (NY)	β	3,275.1	-950.4	229.5	1,306.2	2,402.9	1,166.2
Providence (RI)	α	308,324.3	109,977.1	122,052.0	324,271.0	512,455.2	343,837.9
Providence (RI)	β	7,789.1	-1,131.4	2,691.7	1,961.9	3,091.0	2,257.6
Raleigh (NC)	α	295,061.4	58,774.5	7,456.0	231,780.0	316,270.9	275,038.5
Raleigh (NC)	β	6,804.7	-960.9	2,106.7	1,920.3	4,141.2	1,140.7
Reno (NV)	α	276,831.8	150,438.9	97,235.7	245,451.2	401,947.2	301,749.8
Reno (NV)	β	9,531.9	-121.9	2,251.6	1,937.4	3,320.0	1,323.4
Richmond (VA)	α	386,145.2	121,450.1	-101,863.6	267,275.4	354,915.0	312,843.3
Richmond (VA)	β	2,187.3	-394.6	102.1	1,664.9	2,348.9	1,301.3
Riverside-San Bern. (CA)	α	323,517.6	112,693.5	39,174.6	248,794.4	434,579.4	304,417.2
Riverside-San Bern. (CA)	β	6,462.2	2,195.7	3,682.6	2,547.8	3,010.2	1,956.8
Rochester (NY)	α	168,113.7	53,211.9	107,104.4	158,967.1	276,792.8	172,404.3
Rochester (NY)	β	3,828.9	-10,394.2	1,233.0	1,264.3	1,925.8	1,450.5
Sacramento (CA)	α	329,769.6	140,082.8	24,824.1	294,770.1	471,459.6	337,491.6
Sacramento (CA)	β	7,133.1	3,368.9	3,809.9	2,592.2	3,128.7	2,332.4
St. Louis (MO)	α	148,586.3	67,522.5	-55,834.8	187,064.6	354,183.1	219,519.6
St. Louis (MO)	β	9,432.6	-2,619.5	2,338.6	1,680.1	2,944.2	1,637.6
Salem (OR)	α	255,213.0	124,474.3	28,394.1	237,459.2	415,736.4	265,750.9
Salem (OR)	β	6,209.2	-2,987.9	1,168.7	2,393.5	3,218.3	2,321.8
San Diego (CA)	α	846,866.0	651,733.0	451,682.5	689,547.3	960,114.9	758,414.9

Table A5: Mean Estimated Ticket and Slope Parameters, by Metro

Metro	Coef. Type	Land	Replace Cost	Hedonic	Estimated Services:		
					Land, Area	Land, Rooms	4 + Vintage, Bath
San Diego (CA)	β	8,157.3	1,687.2	-2,027.0	2,323.5	5,048.1	2,538.8
San Francisco-Oakland (CA)	α	677,656.0	574,246.6	73,809.5	753,278.9	1,254,802.0	838,398.8
San Francisco-Oakland (CA)	β	34,598.7	14,355.8	18,429.4	3,336.5	7,339.4	3,669.1
San Jose (CA)	α	717,833.1	662,685.9	350,349.0	884,431.3	1,489,636.0	972,316.2
San Jose (CA)	β	42,165.9	19,109.6	19,898.4	4,758.7	9,214.5	6,101.8
Seattle (WA)	α	636,030.8	389,211.4	4,801.4	557,318.7	677,568.9	608,317.5
Seattle (WA)	β	6,051.4	1,450.0	448.4	2,132.5	4,689.2	2,064.8
Springfield (MA)	α	263,909.4		106,570.3	254,228.4	404,106.2	261,997.0
Springfield (MA)	β	4,333.8		1,641.5	1,512.2	2,621.2	1,874.8
Stockton (CA)	α	291,174.0	94,076.8	58,340.5	230,328.1	370,111.9	262,035.1
Stockton (CA)	β	5,521.5	708.7	2,924.8	2,088.3	2,109.4	1,771.2
Tampa-St. Pete. (FL)	α	150,922.6	63,124.1	-33,426.8	163,350.1	366,198.8	193,121.7
Tampa-St. Pete. (FL)	β	8,866.0	-698.7	2,212.2	2,139.6	3,970.4	2,153.0
Toledo (OH)	α	127,879.9	2,026.9	50,232.8	107,092.9	228,732.0	119,525.1
Toledo (OH)	β	3,436.7	-7,250.9	947.7	1,163.4	1,782.5	1,279.2
Tucson (AZ)	α	274,976.2	78,647.5	-62,497.5	253,309.3	304,914.8	280,464.2
Tucson (AZ)	β	6,070.7	1,003.8	4,027.8	1,806.7	5,570.2	1,412.4
Tulsa (OK)	α	126,263.8	112,345.8	33,702.9	127,096.8	352,344.6	176,615.1
Tulsa (OK)	β	8,698.5	-8,429.6	3,538.3	1,644.7	4,302.4	1,341.2
Norfolk (VA)	α	315,199.8	145,457.0	101,787.7	238,673.5	503,104.7	303,562.0
Norfolk (VA)	β	9,485.3	1,514.6	5,637.4	3,823.5	3,767.2	3,571.7
Washington (DC)	α	499,458.7	317,119.9	-53,338.6	626,854.7	748,950.1	681,482.7
Washington (DC)	β	21,265.8	9,253.2	3,429.9	2,269.4	4,704.8	2,436.4
Wilmington (NC)	α	331,135.8	246,332.2	165,308.5	272,981.3	431,178.2	317,608.0
Wilmington (NC)	β	6,183.1	-2,683.9	3,152.0	3,349.4	3,785.3	2,822.9

Table A5: Mean Estimated Ticket and Slope Parameters, by Metro

Metro	Coef. Type	Land	Replace Cost	Hedonic	Estimated Services:		
					Land, Area	Land, Rooms	4 + Vintage, Bath
Winston (NC)	α	203,209.8	33,118.7	-1,647.3	163,329.6	264,802.7	189,055.9
Winston (NC)	β	3,188.6	-3,353.1	794.6	1,652.8	2,313.5	1,370.5
Worcester (MA)	α	243,348.6	-19,386.7	236,605.7	322,784.1	470,034.8	327,970.3
Worcester (MA)	β	8,354.4	4,973.2	4,124.2	1,090.9	3,589.0	1,625.7

Source: Authors' calculations using housing transactions data as described in Section 4.