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

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Abstract

In speculating that local public goods could be efficiently provided, Tiebout (1956) envisioned head taxes which would both finance public goods and price access to them. In practice, head taxes are not available, potentially leading to distortions. Hamilton (1975, 1976) responded that zoning can mimic a head tax by creating a price (or "admission ticket") at the border. While the debate over the efficiency of the local provision of public goods continues, modern empirical work, including structural models and simple hedonic pricing models, routinely imposes the restriction that amenities are capitalized through the price of land or housing *per unit*. It has ignored the possibility of capitalization into tickets. This paper generalizes previous work to show more precisely how land-use restrictions create tickets. It further advances the literature by using a unique national level dataset of property transactions matched to very local neighborhood amenities to measure the extent to which local public goods are capitalized into "intercept" (ticket prices) versus "slope" effects (varying prices per unit). We find evidence for both, but the intercept effect is strongest when land use regulation is greater, as predicted by the model.

1 Introduction

Since the seminal work of Tiebout (1956), the public finance literature has suggested that local governments may provide local public goods efficiently. Tiebout's basic argument was that if local jurisdictions can finance public goods with non-distortionary head taxes, then households can pick the jurisdiction in which to live based on their willingness to pay for public

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goods. As with a well-functioning market for private goods, the head tax serves as a price on benefits, a price which optimally coordinates the distribution of public goods. Households will sort into communities based on their demands for public goods, with high-demand households together in a high-public good community, low-demand households together in a low-tax community, and so forth. As a price on public benefits, the head tax is a "benefit tax" – that is, a fee for services.

However, jurisdictions cannot realistically use head taxes to finance local public goods. Instead, they typically use property taxes. This departure from Tiebout's idealized model gives 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, Epple, and Romano 2012). 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. In such cases, the entry into the community of a lower-income resident consuming less housing creates a transfer from richer households (with larger houses and, hence, greater property tax burdens). The problem can be viewed as a case of the "tragedy of the commons," in which too many people crowd into a jurisdiction to take advantage of its tax base. Richer households respond by voting for lower tax rates and lower public good levels.

In a simulation model of Tiebout sorting, Calabrese, Epple, and Romano (2012) find that too many people do crowd into the most desirable communities, creating congestion. In fact, in their simulations, this congestion entirely negates any gain from Tiebout sorting processes, with households better off with a single homogeneous community–that is, with no menu of choices over public good levels at all. They find that this jurisdictional choice externality is a much bigger problem then other distortions from the property tax, such as lower consumption of housing capital (Zodrow 2001).

Hamilton (1975, 1976) extended Tiebout's model to account for just such issues (see

Fischel 1985, 2001 for discussion). He argued that, in special cases, zoning can prevent such distortions by preventing too many people from crowding into a community. In this paper, we argue that Hamilton's results are more general than often perceived. Any friction, such as local land use regulations, that places a binding constraint on the number of lots (or housing units) rather than their size introduces a price on lots that mimics a head tax: each jurisdiction will have its own "ticket" price for entry. Thus, housing costs consist of a *two-part tariff,* an entry ticket plus a per-unit cost for additional housing services (see also Glaeser and Gyourko 2003).

A large literature has debated the relative merits of these models and purported to empirically test the Tiebout-Hamilton benefit view of the property tax against the "new view" that it is distortionary (e.g., Fischel 1992, 2001, Mieszkowski and Zodrow 1989, Nechyba 2001, Ross and Yinger 1999, and Zodrow 2001). 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 argue that capitalization is still consistent with the new view of the property tax. Still others have gone further, arguing that, because in Hamilton's (1975) world the price of homogenous land is constant everywhere, capitalization contradicts the benefit view. Indeed, Ross and Yinger (1999) call such evidence "overwhelming," concluding that evidence of capitalization is proof against 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.

Unfortunately, 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.[1] This includes the model of Carroll and Yinger (1994), which restricts the price of land to be uniform per square foot. Most notably, it includes any hedonic study, such as those discussed by Ross and Yinger, that uses logged housing prices as the dependent variable. A typical hedonic model is of the form $ln(p_{in}) = f(g_n) + h(L_i, x_i)$, where i is an individual house, n is a neighborhood, g is a vector of amenities, L is land, and x a vector of other housing characteristics. Such a model imposes the condition that the amenities have an effect on housing values that is proportionate to the housing services index $h()$. Similarly, virtually all equilibrium models of sorting impose the restriction that capitalization is through per-unit housing services (e.g. Bayer et al. 2009, Epple and Sieg 1999) as does the simulation in Calabrese, Epple, and Romano (2012).[2]

In this paper, we first generalize models of capitalization by allowing public goods and amenities to affect both the "ticket" prices and the unit prices of housing services. As suggested by Nechyba (2001), there likely is some truth to both the benefit view and the new view. Accordingly, we propose to account for both through the following family of models:

$$p_{cnit} = \alpha_{cn} + \beta_{cn} h_c(L_i, x_i) + \epsilon_{cnit}$$

where c indexes cities and t time. The terms α and β represent, respectively, the intercept/ticket prices and the slope shifters/housing service gradient prices. If the α are all zero, the model is equivalent to the standard view and the notion of entry tickets to a community is rejected. If the β are all equal, the marginal cost of housing is the same across communities, which would be consistent with Hamilton's model with optimal zoning and only congested public goods. If neither is true–as seems most likely–there is some pricing of public goods

[1]Lutz (2009) offers an important exception. He finds that decreases in the fiscal transfers within a community result in increases in housing capital. On the face of it, this is inconsistent with a simple zoning story in which capital is fixed. However, this too is not a clean test. For example, it is also consistent with a story in which jurisdictions have *minimum* constraints on housing size.

[2]Typically, such models work by first estimating a hedonic regression of the form $ln(p_{in}) = \alpha_n + h(L_i, x_i)$, with the neighborhood fixed effects capturing between-neighborhood differences in the price of housing services due to amenities. There still is capitalization into tickets in the weak sense that there is an affect of amenities even at x=0, but only proportionate to the effect at all values of x.

through entry tickets and some through differential marginal costs for land and housing.

In addition to testing the basic model of two-part pricing, we consider the conditions where capitalization into tickets is more likely to dominate capitalization into land/housing prices. We would expect to find capitalization into tickets predominating in communities with a fixed set of housing units (possibly a highly heterogeneous set), or at least with high transaction costs to reconfigure the housing stock. This hypothesis can be tested using data on the regulatory environment such as the Wharton residential land use regulatory index (Gyourko et al. 2008). Using a difference-in-differences design, we test whether capitalization through "tickets" (relative to that through land prices) is more pronounced in metro areas with tighter zoning regulations than in those with more slack regulations.

To test these hypotheses, we have compiled what we believe to be the most comprehensive hedonic data set ever assembled, combining breadth and depth. We have obtained virtually every housing transaction between 2005-2011 in 95 urban areas the United States, complete with housing characteristics and geocoding to the Census block level. Additionally, we have matched each house to its elementary school attendance boundary 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 also is matched to the data at the city level.

We find strong evidence of the existence of tickets and hence two-part pricing of housing. Moreover, we find that, consistent with our hypothesis, amenities tend to be capitalized into those ticket prices in cities with tighter regulatory controls, whereas they tend to be capitalized into land/housing prices in cities with weaker controls.

Our findings have two key implications for the literature. First, they provide a new interpretation of the old debate between the "benefit view" and the "new view" of the property tax, which seemed to reach an impasse over how to interpret capitalization. Missing from those debates has been the distinction between capitalization into tickets or into housing prices. If zoning is to mimic a head tax then capitalization should be into tickets, not land or housing-services prices. This is precisely our finding. However, the normative implications of our findings should be interpreted cautiously. *If* public goods are congested, a *necessary* condition for efficiency is to price entry into the jurisdiction (Banzhaf 2014). Our findings only show that this condition is met, not sufficient conditions. Moreover, zoning will induce capitalization of amenities into ticket prices whether or not the amenities are congested, raising the possibility of inefficiently high exclusion.

A second implication of our work is that the very large literature on "hedonic" housing prices routinely employs models that are fundamentally mis-specified. This includes basic hedonic models as well as hedonic models employed to find housing prices for use in sorting models.

In general, 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 land prices; in contrast, the possibility of amenities being capitalized through ticket prices is essential to our model. Finally, they do not derive these two measures from a single data source, as we propose to do.

Our model also relates to recent work by Turner, Haughwout, and van der Klaauw (2014) and Albouy and Ehrlich (2016). 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.

2 Conceptual Framework

In a pair of influential papers, Hamilton (1975, 1976) argued that that zoning could replicate the head tax present in Tiebout's (1956) model, thus internalizing the jurisdiction 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 internally homogeneous communities. 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, focus on the specific special cases has obscured the generality of the insights. In this section, we generalize Hamilton's results. First, to set a baseline for comparison, we consider the properties of a hedonic equilibrium with no land-use controls. To see the precise effects of zoning, we distinguish between two cases, restrictions constraining the size of lots (or houses) and restrictions constraining the total number of lots (or housing units). We argue that, relative to no land-use controls, minimum lot sizes limit the heterogeneity of lot sizes in a neighborhood, whereas restrictions on the total number of lots induce two-part prices with "tickets." To emphasize that fiscal transfers are not necessary to generate tickets, we focus on exogenous amenities.

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 0. Neighborhoods are ordered by a scalar-valued composite of exogenous amenities and local public goods, G_n. 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 one neighborhood and, conditional on that neighborhood, the size of a lot to consume. On the supply side, developers allocate land to lots to maximize the value of rents, subject to any land use constraints.[3] The price of a lot l in neighborhood n is a potentially nonlinear function of the size of the lot: $p_{ln} = p_n(h_{ln})$. (Note because G_n is uniform within neighborhoods, we implicitly subsume its affect on prices into the neighborhood-specific price function.)

Consider first for purposes of comparison the case with no land controls and malleable lots. The first-order conditions for profit maximization require that the marginal value of land be the same at each lot within a neighborhood, otherwise developers would re-allocate 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 would develop fewer lots and make the remaining lots bigger, or alternatively if it were lower they would develop more, smaller lots. Thus, without land-use restrictions, the following two equilibrium conditions hold:

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

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

[3] We abstract away from housing capital in the formal exposition of the model but return to it in our empirical work. It would be straightforward to incorporate capital into the numeraire k. Alternatively, if capital stocks are fixed we can think of h itself as a composite of land and capital.

for some constant β_n. Integrating Equation (1a) gives

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

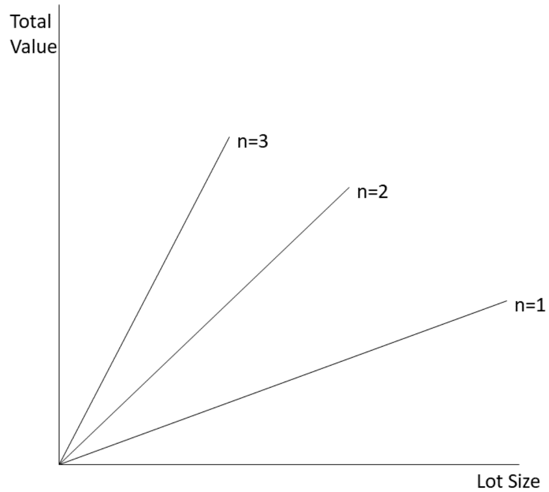
for some constant of integration α_n. Dividing by square footage gives $p_{ln}/h_{ln} = \alpha_n/h_{ln} + \beta_n$. Equation (1b) then requires α_n=0. Consequently, $p_n(h_{ln}) = \beta_n h_{ln}$. That is, because of the no-arbitrage condition at the extensive margin, there are no tickets in the community (for if there were, the average value of land would be higher than the marginal value and developers would prefer to re-arrange their land into more lots). Instead, there is a single price per square foot in the neighborhood, β_n. Additionally, the price per square foot in these 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 an average community. 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 Zoning as Minimum Lot Sizes

Consider now the case where the city adopts land use controls in the form of a minimum lot size $\underline{h}$ and consider the case 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 of course equivalent to the previous sub-section.) Although such restrictions may *affect* density in equilibrium, they are not binding on density, in the sense that total land area divided by $\underline{h}$ is strictly greater than the number of lots when $\underline{h}$ is not binding at all lots. Moreover, developers still can re-arrange land to ensure conditions (1a) and (1b) are met. (If $\underline{h}$ is not

Figure 1: Pricing Under Consensus View of Capitalization



binding at all lots, there is "slack" land in the neighborhood that developers can re-allocate to meet the conditions.) Thus, we still have $p_n(h_n) = \beta_n h_n$.

Conditional on living in neighborhood n, a household maximizes utility subject to the minimum lot size constraint. Ignoring the non-negativity constraint on 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:

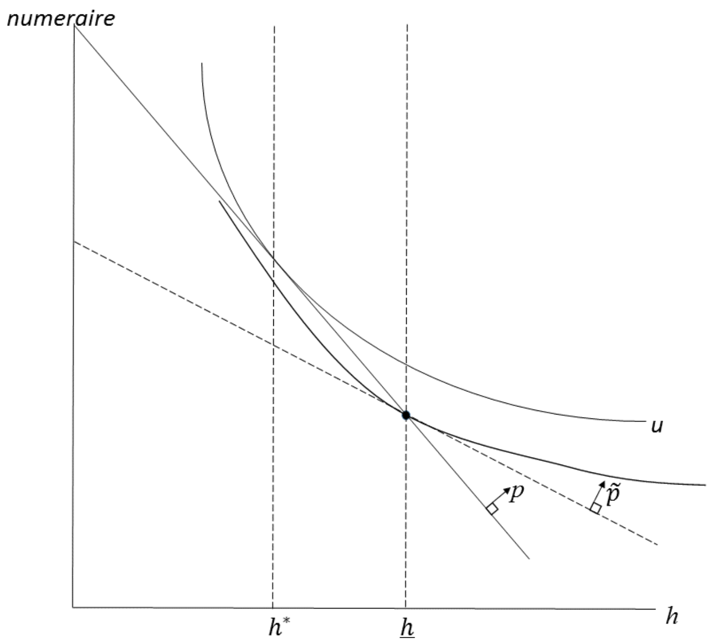
$$\frac{\partial u}{\partial h} = \widetilde{\lambda}\widetilde{\beta_n}. \tag{7}$$

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.[4] 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 2 compares the primal and dual problems. Given prices p, an unconstrained household would choose h^* and achieve utility level u. The constraint requires the household to consume at least $\underline{h}$, creating a wedge between the slopes of p and the indifference curve, of course lowering utility. However, there is a lower price $\widetilde{p}$ supporting the indifference curve at that point. With that lower price (and with income adjusted 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

[4] 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.

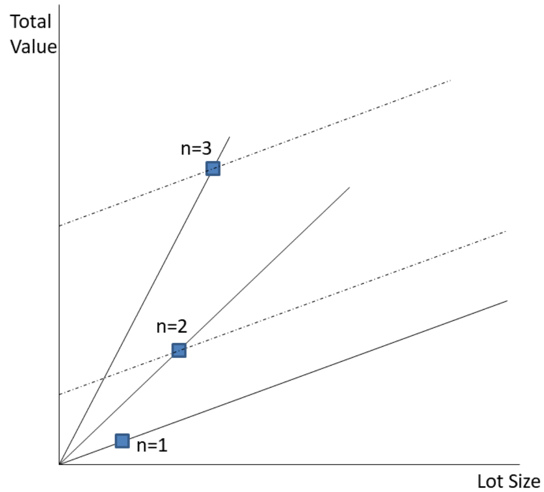
Figure 2: Optimization with Constraint and with Shadow Values



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 recall also income is adjusted downward by $(\widetilde{\beta_n} - \beta_n)\underline{h}$ conditional on choosing the community. Obviously, 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.

Hamilton (1975) 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. In that case, a two-part tariff is observationally equivalent to a simple price. Either price function is consistent with a single data point. Figure 3 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. 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

Figure 3: Pricing Under Hamilton (1975)



into prices, though the values of β_n will differ.

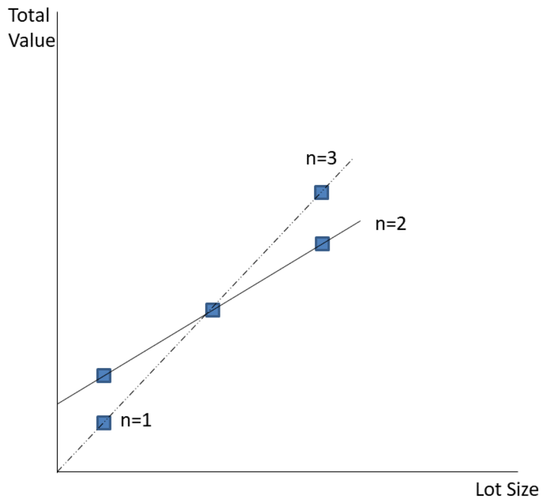
Whether β_n increases or decreases is an empirical question, even abstracting from any effects of lot size restrictions on amenities such as green space and congestion (Glaeser and Ward 2009, Ihlanfeldt 2007). On one hand the restriction per se reduces the utility a household can achieve in the neighborhood, reducing land demand at the extensive margin; on the other hand by its nature it requires more land be consumed by the constrained households, which is equivalent to a a reduction in supply faced by the unconstrained households. If neighborhoods are sufficiently different (as in our model) and if a large number of people are at the constraint, we would expect housing prices to increase, as we find in our simulations. If so, an additional prediction is that the minimum lot sizes reduce the heterogeneity of land consumption. The left tail of the distribution is cut of by the constraint, the right tail is moved in because unconstrained households move up their demand curve as prices increase.

2.3 Zoning as a Transaction Cost on Reconfiguring Lots

But zoning is not limited to restrictions on lot size. Other regulations 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 any myriad of rules and restrictions locking in an older housing stock and division of land, now out of equilibrium, and preventing adjustments (historical preservation, height restrictions, difficulty obtaining permits, etc.). By preventing existing lots from being subdivided or existing single family homes from being replaced by multidwelling units, such restrictions restrict the number of housing units. Consequently, by making housing units scarce per se, in addition to land, they induce a two-part tariff. 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.

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 4. 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 homogenous community of all small lots; likewise the point n=3 represents a homogenous 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 restricts. Now, a small lot in n=2 has an advantage over an equal-sized house in n=1 because it enjoys the tax base of the larger lots. Hence, it is more expensive. By the same token, the large house in n=2 has a disadvantage relative to an equal-sized house 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

Figure 4: Pricing Under Hamilton (1976)



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.

To emphasize this point, 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. TDRs are one transparent example where there is a price on a lot as well as land.

Even without such a formal market, however, the scarcity on lots introduces a shadow price for them. 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 (Glaeser and Gyourko 2003). 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.

As we noted in the previous sub-section, Hamilton's (1975) paper is a special case where a minimum lot size restriction is binding on all lots. Interestingly, that is precisely the case where a minimum lot size restriction is equivalent to a restriction on the maximum number of lots. That is why, as shown in Figure 3, we can characterize the difference in neighborhood housing prices either with land prices or with tickets. In general, lower bounds on lot size enter into land prices and upper bounds on the number of lots require tickets.

Moreover, we would normally expect such 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 increasing 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.

2.4 Simulations

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

$$u_i = (1-\theta_i)\ln(z) + \theta_i \ln(h) + \phi_i G \tag{8}$$

and indirect utility functions

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

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).

We consider three policy scenarios. 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. In the third scenario, we replace the minimum lot size restriction with a restriction on the maximum number of lots, or density restriction (calibrated to be the same as the number of lots in neighborhood 2 in the second scenario's equilibrium. Table 1 and Figures 5-7 summarize data 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

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

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 ϕ (i.e. higher tastes for public goods) sort into the high-G neighborhood, as we would expect. The total number of residents is 9,398, or almost the entire population, with about two-thirds living in the high-G neighborhood.

In Scenario 2, the minimum lot size reduces the total population in the city to 8,453, and especially reduces the density in the high-G neighborhood. Land prices increase in both neighborhoods. Moreover, the heterogeneity in lot sizes decreases, as can be seen in Figure 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 land prices falling and the difference between prices in the

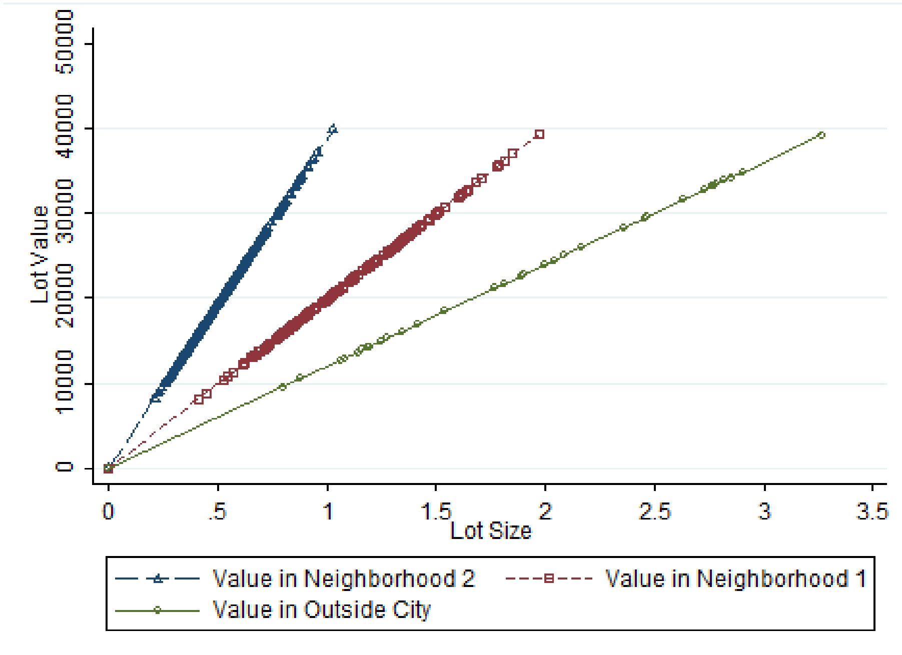


Figure 5: Simulation: No Land-Use Controls

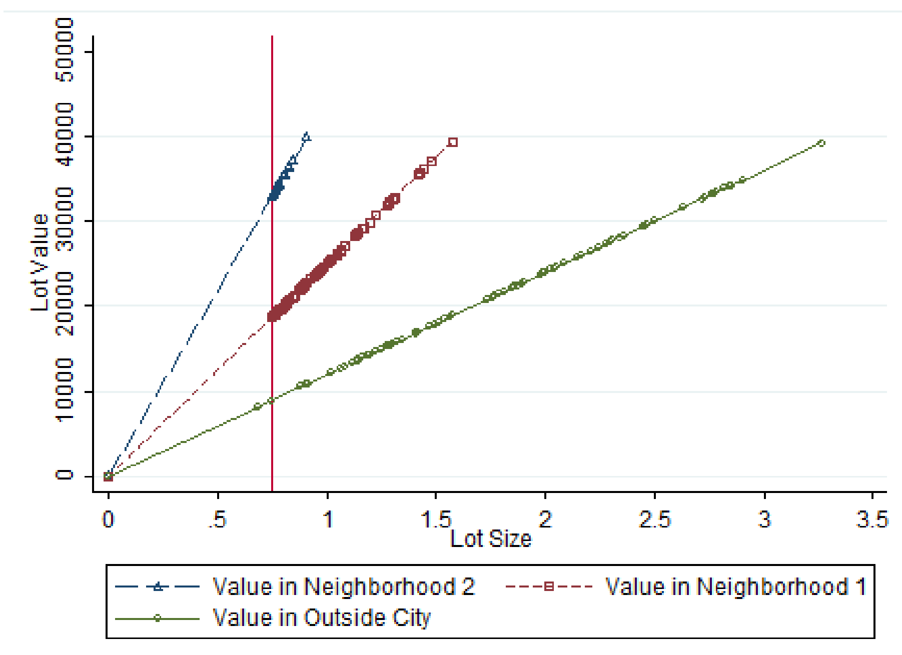


Figure 6: Simulation: Minimum Lot Size

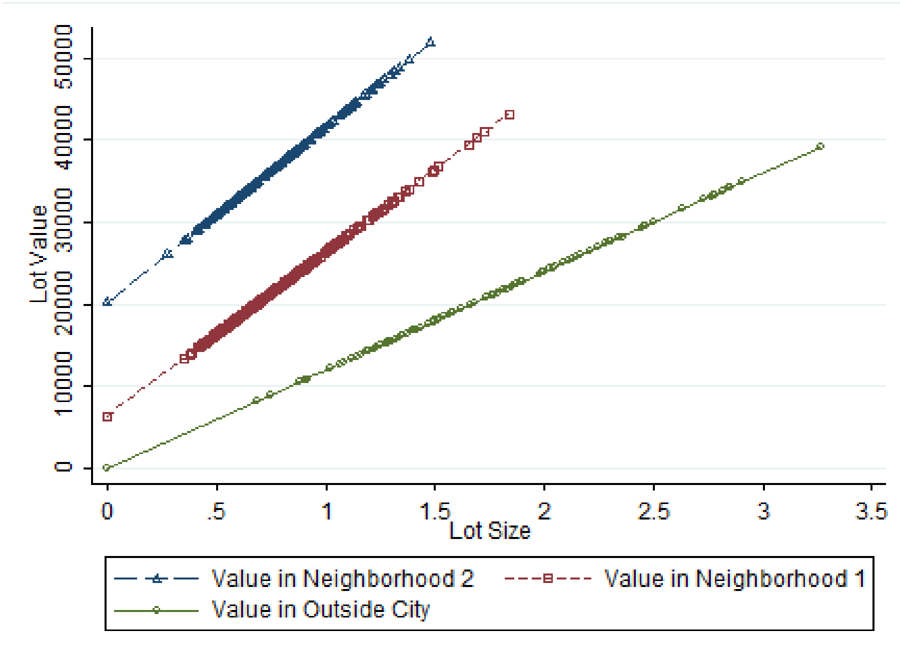


Figure 7: Simulation: Maximum Number of Lots

two neighborhoods collapsing, but we also see the introduction of entry tickets. Figure 7 shows the clear tilting of the price functions, as the intercept becomes non-zero and the slopes decrease. Interestingly, with tickets there is more sorting on ϕ (tastes for G) than in the other scenarios, because now the market prices access to G directly, rather than through land.

3 Empirical Strategy

The above discussion suggests some testable implications to bring to the data. In particular, we look for three patterns.

3.1 Patterns in the Raw Data

The first two patterns involve simple regularities. First, we expect that the between-neighborhood variance in housing values will increase with lot size (or housing services), but less rapidly in heavily zoned cities, especially those with density restrictions. This insight can be seen from a comparison of Figures 1 and 4. Figure 1, without zoning, shows prices fanning out with lot size. Figure 4, with density restrictions, shows a constant difference in the between-neighborhood price differences, regardless of lot size.

Second, we expect that a standard hedonic price regression of the form $ln(p_{in}) = \alpha_n + h(x_i)$, will at small lots (or houses) yield higher residuals in highly zoned cities than in weakly zoned cities, and the reverse at large lots (houses). Again, this insight can be seen by comparing Figures 1 and 4. If Figure 4 is correct, fitting a mis-specified model motivated by Figure 1 will fail to adequately capture the tilt in the price functions, underestimating housing values at small lots and overestimating them at large lots.

Beyond inspecting the patterns of data in these first two ways, our main strategy involves a more formal effort to recover the pieces of the two-part tariff pricing function and to describe the relationship between these prices and local amenities, and how it changes with zoning. This involves two steps: first recovering the prices (including the intercepts α and the slopes β), then exploring how they capitalize amenities and how this capitalization varies by zoning.

3.2 Recovering Prices

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

$$\frac{p_{cnit}}{I_{ct}} = \alpha_{cn} + \beta_{cn} h_c(L_i, x_i) + \epsilon_{cnit} \tag{10}$$

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 deflator from the FHFA.[5] The α_{cn} and β_{cn} terms are the variables of interest: respectively, the ticket and housing series prices. Finally, $h_c(L, x)$ is the housing service function (which may vary by city) of land (L) and a vector of other characteristics x.

Selecting the appropriate housing services function $h(\ )$ is a challenge both conceptually

[5] As an alternative, we also use a deflator estimated with our own data, and achieved similar results. We estimate $p_{cnit} = I_{ct}(\alpha_{cn} + \beta_{cn} h_c(x_i)) + \epsilon_{cnit}$ 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.

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, the function $h(\ )$ either must be estimated or defined *a priori* by the econometrician. The practical issue is that the reporting of these housing attributes varies across counties and metro areas in the sample. While virtually all assessors in our data report lot size, living area, and age of structure, they vary in their reporting of room partitions.

We approach these difficulties three ways. The first is to constrain β_{cn} to differ only for land, while still conditioning on the physical capital characteristics of the property:

$$\frac{p_{cnit}}{I_{ct}} = \alpha_{cn} + \beta_{cn} L_i + h_c(x_i) + \epsilon_{cnit}. \tag{11}$$

Within the scheme of this first approach, we consider three specifications of the control $h_c(x_i)$. The first uses flexible functions of the observed x. In practice, we use linear and quadratic terms for living area, dummy variables for age of structure (in decadal bins), and dummies for the number of bedrooms, bathrooms, and/or total rooms (depending on the available information in each city). The second specification is similar, but uses only those attributes that are available in all counties in our sample (namely, living area and age). The third specification assigns a house with characteristics x_i in city c into discrete categories for which we have estimates of the replacement cost of capital from the RS Means construction cost estimates. 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, 2005) and others.

These specifications allow local public goods to be capitalized into the slope of the land price function as well as a ticket price. Their main advantage is in ease of estimation. However, this tractability comes at the expense of imposing that capitalization occurs only through land, assuming away any capitalization occurring in the physical structure of the property. 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.

Our second approach actually simplifies the previous model by omitting the conditioning on $h_c(x_i)$. If amenities truly are capitalized only into land, as in Equation 11, then clearly this creates an omitted variables problem. But if amenities are capitalized into housing characteristics x as well as land, and if lot size is correlated with the size of a house, in may be better to omit x and simply take L as a proxy for $h_c(L, x)$

In future work, we plan also to consider models in which intercepts occur through housing services generally, and to estimate those services as a function of land and housing capital. Whereas the model above can be estimated on a city-by-city basis, this variant requires estimating a function $h(L_i, x_i)$ that is constant across cities, making it more computationally challenging. Our plan is first to estimate the following equation with non-linear constraints on a small national subsample of the data:

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

where $h(\ )$ is a highly parameterized flexible function. From this initial estimate, we will obtain a consistent estimate of $h()$ which we denote $\hat{h}$. We will then impose that function on the remaining data and estimate

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

Once we have estimated these models, we first test for whether $\alpha_{cn} = 0$ for all n and whether $\beta_{cn} = \beta_c$ for all n. Rejecting the first implies capitalization through tickets. Rejecting the second implies traditional capitalization through unit housing prices. We expect to reject both hypotheses.

3.3 The Pricing of Local Public Goods

The second step is to relate these two forms of prices 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:

$$\hat{\alpha}_{cn} = a_c + (1 + a_Z Z_c)\gamma' g_{cn} + \nu_\alpha \tag{12a}$$

$$\hat{\beta}_{cn} = b_c + (b_0 + b_Z Z_c)\gamma' g_{cn} + \nu_\beta. \tag{12b}$$

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_b terms represent city dummies, which play a dual role. First, as usual, they capture city-wide characteristics such as climate and labor-market conditions as well as the direct effects of land-use restrictions. Second, because we estimated 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).[6] The a_Z, b_Z terms measure the interaction of local public goods with city-level land use restrictions Z. Because the purpose of our study is not to recover the overall hedonic price functions but to test how capitalization into the extensive and intensive portions of the pricing function differs with land use restrictions, α_Z and β_Z are the main variables of interest. The model suggests 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 $a_Z > 0, b_Z < 0$. As we discuss further below, we treat Z both as a scalar (an overall measure of land use restrictions) and as a vector with

[6]Note that we cannot separately identify a_0, and b_0, and all terms of 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 G does not contain a constant term.

two parts, an index of minimum lot size and restrictions that might constrain the number of lots.

4 Data

The starting point for our data is a large data set of national property transactions. We divide these transactions by city, and then sub-divide cities into neighborhoods, which are represented by elementary school attendance zones. We then link these housing data to a rich set of national public goods at this neighborhood level. In this section, we describe these data in more detail.

4.1 Housing Data

The housing data come from the real estate analytics firm Dataquick (since acquired by CoreLogic). 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. (Dataquick's collection method overwrites 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.) The data also include latitude and longitude coordinates of the property, which we use to match the properties to their neighborhood.[7]

We have data on nearly 13.2 million transactions from 2005-2011 at 105 large US cities with nearly 20,000 neighborhoods. 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 partial property sales, subdivisions of parcels, and sales of vacant land. These cuts leave us with normal, market rate transactions. We are additionally interested

[7] We are particularly indebted to Pat Bayer and Chris Timmins, as well as Eduardo Jardim, Gary Thompson, and Joshua Smith for assistance in accessing the data.

in the property characteristics, so we further clean the data of properties with missing or obvious misreporting (parcels and or living areas less than 500 sqft.) 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 in 20,353 neighborhoods.

Table A1 in the appendix reports the data available by city. Table A2 reports summary statistics by metro area for the main variables in the first stage regressions, which is used to get estimates of α_{cn}, β_{cn} from (10).

4.2 Public Goods

Because our empirical include city-specific dummies, we have begun by focusing on four amenities or public goods that vary within metropolitan areas: education, distance to the city center, crime, and environmental quality. (In contrast, climate, arts, and employment vary more between cities than within cities.) Using latitutude and longitude provided in the Dataquick data, we match each property to its US census block. We then assign blocks values of the amenities and aggregate blocks up to neighborhoods.

Among the attributes we consider, public school quality is the one that changes most sharply at discrete boundaries. Accordingly, we use school boundaries to define neighborhoods. In particular, we have collected a national set of school zone maps, with 4th grade school attendance boundaries for the entire country, through the School Attendance Boundary Information System (SABINS) (The College of William and Mary and the Minnesota Population Center 2011).[8] Using these SABINS maps and GIS software, we were able to place 60.3% of Census blocks (comprising 69 percent of our housing transactions) into their 2010 4th grade school attendance boundary. For the remaining observations, we first assigned the blocks to their school district and then to the nearest school within the district, as in Downes and Zabel (2002). Recent work by Reinhardt (2016) suggests such a procedure works

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

well and creates little measurement error. 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. (In principle, teacher-student ratios are also available, but only for about 58% of schools.)

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. Dallas and Fort Worth, Texas), we use distance to the closest.

We also obtained two environmental variables. First, as a measure of air polluiton, 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- and 5 km 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 Investigations Uniform Crime Reports database from each local jurisdiciton 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.

Many of these amenity variables are correlated with one another. Our main goal is to derive an index of local amenities, not to derive willingness to pay estimates for each separate attribute.

Table 2 reports summary statistics across all metro areas for our amenity variables. Table A3 in the appendix reports summary statistics for our amenity variables by city.

Table 2: Summary Statistics For Local Public Goods & Zoning Data

Attribute	Mean	StDev	Min	Max
Math Test Scores	0.263	0.829	-3.77	3.65
Distance to Tallest Bldg (km)	22.1	80.9	0.29	1,028.9
Ozone Nonattainment Days	3.57	9.85	0.00	82.28
CERCLA Sites wi 3 km	0.12	0.42	0.00	8.65
Crime Rate	3,515.3	1,611.0	324.2	15,191.3
Wharton Reg. Index	0.2079	0.5744	-1.453	1.870

NOTES: Statistics are taken across all neighborhoods in all metro areas for the final sample of 19,620 neighborhoods.

4.3 Zoning Data

As an indicator of the restrictiveness of zoning Z, we use the Wharton residential land use regulatory index (WRI) (Gyourko, Saiz, and Summers 2008). These data have been widely used in peer-reviewed work for similar purposes. This index is based on surveys of local jurisdictions. We use the metro-wide measure of zoning since the municipality with zoning/regulatory authority in most cases does not correspond to the scholar attendance boundary. In our view, the individual jurisdictions that respond to the survey are best thought of as a random sample representing their municipality.

The WRI is broken down into a variety of indicators, which we use to split land use controls into those binding on lot sizes and those binding on the number of lots. For the former, we use the Density Restrictions Index (DRI) which is an indicator at the local jurisdiction for minimum lot sizes greater than or equal to one acre, and which we average up to municipality level.[9] For the latter, we use the WRI purged of this DRI sub-index, so that the remainder includes measures of political and court involvement, open space rules, and approval delays. This indictor can be thought of as representing the general difficulty of adjustments to the

[9]We also experimented with our own versions of a density restrictions index using the micro data in Gyourko et al (2008), with similar results.

housing capital stock and hence to the number of lots and/or housing units. Our model predicts public goods will be capitalized into tickets especially in cities where this second sub-index is high. An alternative perspective on the WRI is that these sub-indices should not be drawn too finely, and that they are all best thought of as indicators of overall land use restrictions. Accordingly, we also consider the overall WRI.

The last row of Table 2 reports reports the summary statistics for the index across cities in our sample. It is (roughly) mean-zero, with positive values indicating more regulation. Table A3 in the appendix reports the WRI for each city in our data. A few cities for which we have transactions and amenity data lack an estimate of WRI and must be excluded from our second stage regressions specified in Equation (12a) and (12b).

5 Results

5.1 Patterns in the Raw Data

Before coming to our regression results based on Equations (11), (12a), and (12b), we first test for simple patterns in our data consistent with our hypotheses.

5.1.1 Housing Stock Similarity Within Neighborhoods

Our first prediction is that land use regulation homogenizes the housing stock within communities. To test this, we measure the within-neighborhood variance in lot size, by metro area, and compare it to the metro-wide measure of regulation. In this exercise, we use *all* housing stock from the tax assessor data, not only the homes that transact. However, because for computational reasons we cannot map all such properties to school attendance zones, for this exercise we use the census block group as the definition of neighborhoods. This definition does not pose a problem, however, as for purposes of this exercise we are merely trying to measure the component of variance due to a contiguous measure of space, not to map local amenities. Using this full set of properties, we decompose, by city, the variance in housing stock attribute x due to within-neighborhood variation and between-neighborhood variation.

Table 3 reports a summary of the within-neighborhood variance for lot size, living area, and year built across our sample of cities that have WRI data. On average, 60 percent of the variance in lot size is due to within-neighborhood variation (40 percent attributable to between-neighborhood variation). The lower panel reports the results from regressing the city's within-neighborhood variation on the city's regulation index. The first column shows that higher regulation is associated with less within-neighborhood variance; that is, neighborhoods have are more homogeneous parcels in regulated cities. A standard deviation increase in regulation is associated with about a one-third standard deviation decrease to residual variance (0.0356/0.0951). Column 2 adds the subindex for minimum lot size and the average year built for the housing stock city-wide. These do not affect the WRI coefficient and themselves show no significant relationship to residual lot size variance. This is a bit surprising, especially for the minimum lot size index, as it directly cuts off the lower support of the lot size distribution. It is possible that the mere existence of a lower bound on lot size would not substantially homogenize neighborhoods if few lots are at the constraint. Also, the lot size/density subindex may be measured with more error than the wider regulation index. In any case, the results suggest to us that the broad measures of "frictions" are good candidates for testing the theory.

Columns 3 and 4 examine living area and columns 5 and 6 examine year built. There is more within-neighborhood variation in home size than lot size, about 73 percent of the total variance on average. As with lot size, more regulated cities show less within-neighborhood variance (more homogeneity) in home size, although the regression estimate is somewhat noisy. For the age of stock, about half the variance in year built in attributable to the neighborhood. Regulations do not apparently contribute to this. However, column 6 shows that the average age of the stock is significantly negatively associated to within-neighborhood variance. That is, newer cities have more similarity in vintage within neighborhood, which is consistent with more recently developed neighborhoods (such as suburbs) being built all

Table 3: Variance Decomposition Analysis of Housing Stock Attributes

	1	2	3	4	5	6
	Lot Size		Living Area		Year Built	
Summary						
Mean, within-neighborhood variance	0.6085		0.73014		0.52370	
Std Dev	0.0951		0.09181		0.11606	
City Level Regressions						
City Reg Index	-0.0326	-0.0312	-0.0178	-0.0170	0.00752	-0.0000
	(0.01533)**	(0.01567)**	(0.01467)	(0.01507)	(0.01868)	(0.01827)
City MLS Index		0.04025		-0.0223		0.06184
		(0.05602)		(0.05486)		(0.06652)
City Year built		0.00024		0.00043		-0.0029
		(0.00084)		(0.00083)		(0.00100)***
Cons	0.60764	0.08655	0.72939	-0.1084	0.52401	6.23788
	(0.00978)***	(1.67561)	(0.00956)***	(1.64047)	(0.01218)***	(1.98900)***
R^2	0.0485	0.0548	0.0161	0.0213	0.0018	0.0996
J	91	91	92	92	92	92

NOTES: Standard Errors in Parentheses. ***Significant at 1% level, **5%, *10%

at once. In summary, we find that regulations materially homogenize the stock of housing, especially lot size, within neighborhoods

5.1.2 Evidence of Ticket Capitalization

We first explore the data for regularities that would be consistent with the presence of tickets before proceeding to the formal test of amenity capitalization via tickets.

Tickets are an extensive margin price for the right to access to housing services. That is, in the presence of tickets, even an arbitrarily small amount of housing services in a desirable neighborhood commands a price. There is, of course, no observed “arbitrarily small amount of housing services, but a practical way to test for a pattern in the data consistent with tickets is to compare the ratio of prices for smaller and larger amounts of housing services. The higher is the ratio, the more the contribution of the ticket (intercept) to the price of housing.

The thought experiment is to take two properties of different size and place them about neighborhoods in the metro area, comparing their relative prices by the different neighborhoods price functions. We use the first stage regression estimates to construct the predicted price of a property at the 25^{th} and 75^{th} percentiles of the housing services distribution according to our various models of housing services. The amount of housing services offered within a particular neighborhood is endogenous and is in part the outcome of the zoning regime. Thus we calculate the housing services distribution at the metro level as well as within the neighborhood level for comparison.[10] We then calculate the 25-75 price ratio for each neighborhoods housing price function.

Table **??** contains the results for three models of housing services. The predicted prices are the neighborhoods ticket plus the estimate slope times the 25^{th} or 75^{th} percentile point in the distribution of lot size. For the models that remove the capital component (hedonic and construction cost models), we add back the predicted amount of capital contribution to house price for lots in the lower or upper half of the distribution.

The table shows that for the hedonic model using the metro level lot size distribution, a 25^{th} percentile-sized property costs on average 73 percent as much as the 75^{th} percentile-sized property. For the neighborhood level lot size distribution, the smaller property is 87 percent of the larger property price. The larger ratio reflects properties being more similarly sized within neighborhoods than across the entire metro area. The lower panel then reports a regression of the neighborhood price ratios on the metro level zoning index. The positive coefficient indicates that the ratio increases in more heavily zoned areas. A one standard deviation increase in the zoning index implies a seven percent larger 25-75 ratio. That is, the ticket component of the price function comprises a greater contribution to pricewith the slope component contributing relatively lessas zoning increases. This is consistent with the "tilting of the price function as suggested by Hamilton and depicted in Figure 4. The results are largely similar with the construction cost model. The land only model is not as clear, although this makes no adjustment at all for the capital improvement to the property.

While this results suggests the presence of tickets and the role of zoning in producing

[10] This is also a reason to use the regression estimates rather than raw data, so that we compare price functions for properties of arbitrary size.

Table 4: Neighborhood Component of Variance in Property Value, by Property Size

	1	2	3	4	5	6
Model:	Hedonic		Construction Cost		Land Only	
Percentiles By:	MSA	N'hood	MSA	N'hood	MSA	N'hood
Mean	0.7353	0.8644	0.6959	0.7741	0.7904	0.8588
SD	0.7414	0.6786	0.3419	0.2038	0.2278	0.1738
Regression						
WRI	0.0725	0.0247	0.0847	0.0459	-0.010	-0.000
	(0.0100)***	(0.0092)***	(0.0043)***	(0.0026)***	(0.0029)***	(0.0022)
Constant	0.7207	0.8594	0.6782	0.7645	0.7924	0.8588
	(0.0059)***	(0.0054)***	(0.0026)***	(0.0015)***	(0.0017)***	(0.0013)***

them, note that it is not actually a test for *capitalization* of local amenities via tickets or slopes. One needs a measure of local amenities to conduct such a test, so we view this a suggestive evidence, while the formal test of the conceptual framework derives from our econometric model in 12a,12b.

The second regularity is that the ubiquitous semilog hedonic price model, which imposes an effect of capitalization proportional to the amount of housing services, would be, in the presence of tickets, misspecified in a predictable way. In particular, if the true model involves tickets, forcing capitalization to be proportionate to land and/or housing services should under-predict the values of smaller properties and over predict the values of larger ones.[11] To test this conjecture, we run a standard semilog hedonic price regression, accounting for property characteristics and neighborhood fixed effects, and recover the residuals for each property. We then regress these residuals on indicator variables for large and small properties, again first cutting only by lot size and then by lot size and living area jointly.

The results are reported in Table 5. Column 1 shows that the value of small lot properties is under predicted by about seven percent, and large properties over predicted by about eight (minus seven plus 15) percent. Splitting by land and living area in column 2, we see that the misspecification is more pronounced when comparing small lot/small house properties

[11] To be clear, the log price hedonic model does not disallow a shift in neighborhood intercept. Rather, it imposes that any such shift also proportionally tilts the price per unit as well.

Table 5: Residuals From Log Price Hedonic Model

	1	2	3	4
Cons	-0.071	-0.121	-0.075	-0.122
	(0.0002)***	(0.0002)***	(0.0002)***	(0.0003)***
Large Lot	0.1509		0.1579	
	(0.0003)***		(0.0003)***	
Small Lot, Large Home		0.1278		0.1240
		(0.0004)***		(0.0005)***
Large Lot, Small Home		0.0999		0.1084
		(0.0004)***		(0.0005)***
Large Lot, Large Home		0.2653		0.2663
		(0.0004)***		(0.0004)***
Small Lot X City Reg. Index			-0.004	-0.003
			(0.0004)***	(0.0004)***
Large Lot X City Reg. Index			0.0045	0.0043
			(0.0004)***	(0.0004)***

NOTES: Standard Errors in Parentheses. ***Significant at 1% level, **5%, *10%

to large lot/large house properties. Thus, the misspecification is predictably related to the amount of housing services. Columns 3 and 4 go another step further, interacting the city's regulation index separately for small and large lot properties. We find that the pattern of underprediction for small lots and overprediction for large lots is more pronounced in cities with greater regulation, as predicted by our model. These results are fully consistent with capitalization through tickets and cast some concern over the use of the semilog hedonic price model.

5.2 Recovering Prices

Our main empirical tests rely on estimates stemming from the property value regression model, (11), which yields the α (intercept, or "ticket") and β (slope, or unit price) coefficients for each neighborhood in each city in our data. As an initial matter, we test statistically whether there is evidence of capitalization through each channel. Our preferred specification of the land price function (we present others below) includes separate city dummies for the αs and βs, and controls for housing capital characteristics (living area and age and, where available, bathrooms, bedrooms and total rooms) in the first stage using a flexible hedonic function (in levels, of course, not logs).

The test for equality of β is rejected at the 0.01 percent level for 103 of the 105 cities in our sample.[12] As expected, some capitalization of local public goods comes through differences in the unit price of land.

The test for equality of α is rejected at the 0.01 percent level for 98 of the 105 cities in our sample.[13] This indicates that a statistically significant amount of price variation between neighborhoods come through differences in the intercept; hence, some capitalization comes through ticket prices.

We can test the significance of individual α coefficients, though the theory offers no prediction on their particular values. Instead, the model predicts that better neighborhoods (in terms of G) will have greater α to the extent that capitalization occurs in ticket prices. So we are interested in whether some of these are non zero, which would be evidence that at least some capitalization occurs via a ticket. Testing the coefficients individually, we find that all cities but two have at least one neighborhood with an α statistically different from zero.[14]

In summary, we find evidence for capitalization via both channels. Next, we examine whether this pattern varies with regulatory frictions in a way consistent with our model.

5.3 The Pricing of Local Public Goods

Our main empirical test of the model is through the regression model of (12a), (12b), using estimates from the first stage model, (11). The results from these regressions are presented in Table 6. Each column of the table represents a separate specification. All the reported specifications use the FHFA index to deflate prices and use heteroskedastic-robust standard

[12]Failure to reject is likely a lack of power. The two cities that do not reject are Myrtle Beach, SC, with 22 neighborhoods and 13,566 transactions, and Huntsville, AL, with 21 neighborhoods and 1,542 transactions.

[13]The cities that fail to reject (with counts of neighborhoods and total transactions) are: Mobile, AL (3, 46) (Mobile is dropped from our second stage regression.); Huntsville, AL (21, 1,542); Myrtle Beach, SC (22, 13,566); Columbia, SC (83, 15,762); Tulsa, OK (118, 66,155); St. Louis, MO (308, 156,251); Denver, CO (398, 236,002). For all except the last two, we suspect a lack of power.

[14]The cities without any nonzero α's are Myrtle Beach, SC, and Dover, DE.

errors. The first column is our preferred specification, with first stage model as noted above, and weights for the second stage observations by the inverse of their standard error. Our key estimates of a_Z and b_Z are largely consistent with the model. Our estimate of a_Z is 0.65 and highly statistically significant, whereas our estimate of b_Z is small in absolute value and statistically indistinguishable from zero. This suggests that a unit increase in the index G (conditional on the city's mean) increases the value of a neighborhood's ticket price by an additional \$0.65 for every unit increase in the Wharton Regulatory Index Z. In contrast, an increase in the Wharton Index does not affect the capitalization into land prices (although it does not decrease them either). Our estimate of b_0 merely adjusts the scale of G (which is normalized such that a 1-unit increase in G increases a ticket by \$1 at the mean value of Z) into the price per 1000 square feet of land. It suggests a 1-unit increase in G increases the price per square foot by 0.8 cents, or \$16 for 20,000 sq ft lot, so at the mean Z there is more capitalization into land than into tickets. Finally, the individual components of the G index are sensible. At the average value of the Wharton Index, a one point increase in the normalized z-score on the state's math test increases housing prices by \$24,599 at the extensive margin, plus \$186 per 1,000 square feet of lot area (=0.00757*24,559). The parameters on distance to the city center (represented by the tallest building), air pollution (ozone days), and crime rates are all negative and statistically significant, as one would expect. The coefficient on the number of CERCLA sites is negative, though not statistically significant (p=.15) at standard levels.

Figure 8 illustrates the estimated relative effect of an increase in G (from a value of the index at the 25$^{\text{th}}$ percentile of the neighborhood distribution to the 75$^{\text{th}}$), for a relative low value of the Wharton Index (at the 25$^{\text{th}}$ percentile) and high value (75$^{\text{th}}$ percentile) respectively. To emphasize the difference-in-differences nature of our identification strategy, the vertical axis plots the *change* in housing prices from a reference scenario (i.e. the reference location would have a normalized horizontal price line through the origin in the figure). The dashed line shows the effect of the increase in G at the low value the Wharton Index. It

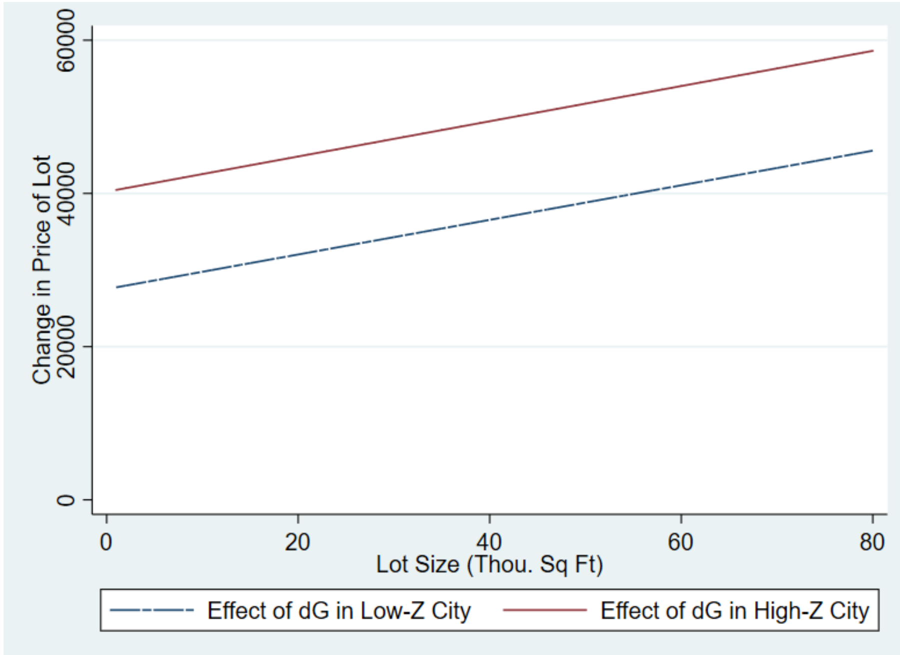


Figure 8: Estimated Change in Housing Prices from Change in G, for Low- and High-Z Cities, Respectively

shows that even here there is substantial capitalization into tickets (the intercept) but also into land prices (the slope). The solid shows the effect at the high value of the Wharton Index. As predicted by our theoretical model, capitalization into tickets is now stronger, with the line shifting up but, somewhat surprisingly, we find that capitalization onto land is no less, with little change in the slope ($b_Z \approx 0$).[15]

The remaining columns report the results from alternative specifications. Column (2) omits the city dummies, replacing them with a constant term and a linear interaction with Z. This actually has little effect on our estimates of a_Z and b_Z, but changes the parameters of the G index, flipping the signs on CERCLA sites and ozone. Such effects are unsurprising as we do not control for city-level amenities like climate. The next two columns consider alternative weighting schemes. Column (3) weights by the square-root of the neighborhood's first-stage sample size; Column (4) weights all neighborhoods equally. The results are gener-

[15] Although we emphasize the importance of city dummies to our identification strategy, it is interesting to note that we do find that the city-specific b_c terms are lower in cities with greater values of the Wharton Index, suggesting a flattening of the overall price function as predicted by our model. In other words, it appears that the plotted *changes* in prices shown here are off of a flatter baseline price line for the high-Z cities.

Table 6: Second Stage Regression of Tickets and Slopes

	Model							
Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
a_Z	0.65012 (0.0868)***	0.72674 (0.0844)***	0.68325 (0.0598)***	0.71284 (0.0787)***		0.54498 (0.0457)***	0.66459 (0.0752)***	0.43808 (0.0369)***
$a_{Z=lotsize}$					0.01058 (0.2228)			
$a_{Z=-lotsize}$					0.66249 (0.0887)***			
b_0	0.00757 (0.0010)***	0.00331 (0.00088)***	0.07024 (0.01244)***	0.08253 (0.0167)***	0.00821 (0.0015)***	0.04946 (0.0099)***	0.12102 (0.0267)***	0.02918 (0.0123)**
b_Z	0.0002041 (0.00148)	-0.0008698 (0.00140)	0.0068104 (0.01513)	0.0014384 (0.0161)		-0.0067827 (0.01285)	0.01502 (0.0265)	-0.05705 (0.0164)***
$b_{Z=lotsize}$					-0.0033575 (0.003600)			
$b_{Z=-lotsize}$					0.0010028 (0.001249)			
γ_{math}	24,599.5 (1,399.3)***	18,236.9 (1,226.3)***	43,746.2 (2,833.1)***	44,952.8 (3,733.0)***	24,655.2 (2,105.2)***	53,314.9 (2,905.8)***	49,773.3 (3,734.2)***	65,627.0 (3,824.3)***
γ_{dist}	-446.78 (69.7)***	-27.729 (6.27)***	-1,463.7 (243.2)***	-1,288.2 (272.2)***	-439.38 (72.1)***	-1,212.8 (194.27)***	-1,433.4 (241.5)***	385.14 (267.4)
γ_{cercla}	-3,183.2 (2,187.3)	4,144.9 (2,152.1)*	-5,159.2 (5,046.9)	-3,939.9 (7,873.8)	-3,023.1 (2,189.1)	-7,218.2 (5,346.5)	-6,145.6 (6,194.9)	-12,947.6 (6,839.5)*
γ_{ozone}	-306.26 (97.82)***	77.069 (40.74)*	-1,088.0 (177.2)***	-828.76 (193.0)***	-301.03 (98.04)***	-1,497.7 (185.3)***	-1,223.7 (223.5)***	-724.11 (234.0)***
γ_{crime}	-3.5601 (0.893)***	-8.8593 (0.613)***	1.9279 (1.5645)	0.06702 (2.2616)	-3.5236 (0.919)***	-3.4817 (1.641)**	0.70215 (2.0440)	-12.858 (1.98)***
Capital Controls	Hedonic	Hedonic	Hedonic	Hedonic	Hedonic	Common	Replace't Cost	None
City Dummies?	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Weighting	SEs	SEs	$\sqrt{N}$	None	SEs	$\sqrt{N}$	$\sqrt{N}$	$\sqrt{N}$
N	38,375	38,375	38,473	38,473	38,375	38,473	37,682	38,184

NOTES: All specifications deflate prices using the FHFA price index. Huber White Standard Errors in Parentheses. ***Significant at 1% level, **5%, *10%.

ally robust to these alternatives. Column (5) breaks the Wharton Index into two components. The first is the DRI Index of Gyourko et al. (2008), which captures restrictions on minimum lot size of at least one acre (at the jurisdiction level and averaged up to the metro area). The second is the overall Wharton Index purged of this sub-index. As discussed in our theoretical model, we expect the first to affect land prices (ambiguously) without creating tickets, whereas we expect the frictions created by the remaining portions of the index to create tickets. The results shown in Column (5) are consistent with this hypothesis. Minimum lot sizes have essentially no effect on capitalization into tickets, whereas the indicators of frictions do. Neither indicator has any discernible effect on capitalization into land prices. We also considered alternative indicators of minimum lot size (including an indicator for any such regulation and an average of the acreage required), finding broadly similar patterns. Columns (6)-(8) consider alternative treatments of controls for housing capital. Column (6) restricts the set of hedonic controls to flexible functions of living area and age, which are available in all cities; Column (7) alternatively subtracts the RS Means estimates of construction costs. The results are broadly robust to these alternatives.

Finally, column (8) omits all controls for housing characteristics. If such characteristics are correlated with lot size, then this specification can be thought of as a crude effort to allow capitalization into overall housing services (proxied by land) and not just into land after conditioning on capital. The results are quite suggestive. The estimated effect of zoning on tickets is now somewhat lower, but still statistically significant. On the other hand, we find more capitalization into land prices than, say, Column (1) at the mean level of Z, but now a statistically significant decrease in that capitalization by Z ($b_Z < 0$), as predicted by our model. This suggests it may be important, in future work, to consider capitalization into the entire housing bundle of land and capital more rigorously.

6 Conclusions and Future Work

This paper addresses how local public goods are capitalized–whether through ticket prices, or the slope of the land/housing price function. Not surprisingly, we find some evidence of both. Most importantly, we find empirically that more restrictively regulated cities exhibit more capitalization in ticket prices (intercepts), and less in the slope of the land price function. Hence, regulation seems to induce a two-part tariff to the capitalization of local amenities.

To this point, we have restricted capitalization into land only. In future work, we will consider capitalization into a function of housing services as well. We also will consider focusing on a small sample of cities with detailed zoning data varying within the metropolitan area.

Our main contribution has been to increase our understanding of how capitalization of amenities "works" in the presence of zoning (and, vice versa, the effect of zoning on capitalization). Beyond this basic point, our work has three further implications. First, it lends additional insights into why the semilog hedonic model may so often be a preferred functional form in empirical work, as well as the limitations of this specification.[16] 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 mis-specified 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 5 suggests this concern is not just academic.

Second, many structural sorting models adopt a discrete-continuous framework in which households 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) (e.g. Bayer et al. 2007, Sieg et al. 2004, Kuminoff 2012; see Kuminoff, Smith, and Timmins 2013 for a review). Invariably such studies assume housing services are purchased

[16] see Kuminoff et al. (2010) for discussion of hedonic specifications.

solely on a per-unit basis, without tickets (typically by first estimating a semilog hedonic model to recover community-specific price indices). One of the empirical regularities such models confront is the surprising degree of income heterogeneity within jurisdictions, which is greater than one might expect from Tiebout's model. Empirical sorting models often explain this result with dispersed distributions of unobserved tastes for amenities, tastes which often are estimated to be slightly negatively correlated with income. However, this result may be forced on the models through the mis-specification of assuming price relationships like Figure 1. Essentially, the models must confront the fact that some richer households are (seemingly) willing to live in a community with poorer households and pay the same marginal price for housing as those households. The models explain this by assigning them low tastes for public goods, so that they are not willing to join a richer community. However, an alternative explanation, consistent with tickets, is that in fact they are paying a lower price for housing in that community than assumed by the model. Some richer households are in lower-ranked communities, not because of a low unobserved taste for public goods, but because they pay less for the large houses there.[17]

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). Our results are consistent with the notion that zoning creates such a price. We take a broad view on the congestibility of public goods and amenities. Air quality, for example, typically taken

[17]This conjecture also is consistent with the low price elasticities estimated by Sieg et al. (2004), which may stem from assuming "too much" variation in housing prices.

for a pure public good, is congestable (hence rivalrous) in the context of community choice. 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). 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 or not, 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.

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A Data and Summary Statistics

Table A1: Data Available by Metro Area

					Rooms Reported?		
City	CBSA code	Neighborhoods	Transactions	Properties	Beds	Baths	Total
Akron_OH	10420	110	56,658	46,416	1	1	0
Albany_Schen_NY	10580	137	68,700	55,984	1	1	0
Allentown_Be_PA	10900	93	54,534	46,274	1	1	0
Atlanta_GA	12060	631	433,873	319,767	1	1	0
Augusta_Aike_GA	12260	81	41,910	33,979	1	1	0
Austin_TX	12420	229	31,336	30,070	0	1	0
Bakersfield_CA	12540	20	78,018	60,259	1	1	0
Baltimore_MD	12580	389	217,031	174,942	0	1	0
Bend_OR	13460	24	28,556	21,929	1	1	0
Birmingham_AL	13820	34	17,503	14,819	0	1	0
Boston_MA	14460	616	259,814	214,129	1	1	0
Boulder_CO	14500	47	26,915	22,626	1	1	0
Bridgeport_CT	14860	150	55,110	47,630	1	1	0
Buffalo_Niag_NY	15380	152	91,335	72,938	1	1	0
Fort_Myers_C_FL	15980	31	176,513	129,706	1	1	0
Charleston_N_SC	16700	60	48,087	39,684	1	1	0
Charlotte_Ga_NC	16740	178	165,449	135,909	1	1	0
Chattanooga_TN	16860	64	37,613	30,328	0	0	0
Chicago_Gary_IL	16981	426	233,166	185,372	0	1	0
Chicago_Gary_IL	16982	291	175,653	148,385	0	1	0
Chico_CA	17020	21	15,133	12,572	1	1	0
Cincinnati_OH	17140	249	158,519	126,255	1	1	0
Cleveland_OH	17460	307	170,691	142,314	1	1	0
Colorado_Spr_CO	17820	118	72,666	58,160	1	1	0
Columbia_SC	17900	117	67,871	54,831	1	1	0
Columbus_OH	18140	283	157,036	130,312	1	1	0
Corvallis_OR	18700	15	6,092	5,122	1	1	0
Dallas_Fort__TX	19100	766	26,649	26,086	1	1	0
Dayton_Sprin_OH	19380	115	63,155	50,793	1	1	0
Daytona_Beach_FL	19660	46	62,673	50,368	1	1	0
Denver_Bould_CO	19740	417	280,547	221,154	1	1	0
Des_Moines_IA	19780	93	57,732	46,433	1	1	0
Detroit_MI	19820	481	199,780	163,413	0	1	0
Dover_DE	20100	20	14,345	12,607	1	1	0
Durham_Chapel_Hill_NC	20500	64	40,903	34,460	1	1	0
Eugene_Sprin_OR	21660	66	27,037	21,986	1	1	0
Fayetteville_NC	22180	48	28,642	23,578	1	1	0
Fresno_CA	23420	171	44,041	35,628	1	1	0
Gainesville_FL	23540	24	24,017	19,890	1	1	0
Grand_Juncti_CO	24300	25	20,332	15,451	1	1	0
Grand_Rapids_MI	24340	23	4,402	3,561	1	1	0
Greensboro_W_NC	24660	106	41,062	34,717	1	1	0
Greenville_S_SC	24860	70	59,412	45,546	1	1	0
Harrisburg_L_PA	25420	89	33,377	28,170	1	1	0
Hartford_Bri_CT	25540	180	77,193	66,296	1	1	0
Huntsville_AL	26620	48	25,267	21,780	0	1	0
Jacksonville_FL	27260	157	181,748	144,363	1	1	0
Knoxville_TN	28940	78	61,073	48,336	1	1	0
Lakeland_Win_FL	29460	64	91,375	69,471	1	1	0
Lancaster_PA	29540	81	37,666	32,083	1	1	0
Las_Vegas_NV	29820	201	303,784	236,122	1	1	0
Lincoln_NE	30700	47	22,310	18,967	1	1	0
Little_Rock__AR	30780	115	41,454	34,454	0	1	0
Los_Angeles__CA	31101	970	434,348	353,084	1	1	0
Los_Angeles__CA	31102	259	109,518	90,245	1	1	0
Manchester_NH	31700	56	29,050	22,325	1	1	0
Medford_OR	32780	33	17,915	14,446	1	1	0

Memphis_TN	32820	148	111,061	84,565	1	1	0
Miami_Hialea_FL	33100	448	753,685	580,593	1	1	0
Milwaukee_WI	33340	1	56,999	47,208	1	1	0
Minneapolis__MN	33460	351	310,390	246,630	1	1	0
Mobile_AL	33660	51	22,881	18,392	1	1	0
Myrtle_Beach_SC	34820	24	60,632	48,464	1	1	0
Naples_FL	34940	30	72,922	58,173	0	0	0
Nashville_TN	34980	202	192,891	152,238	0	1	0
New_Haven_CT	35300	155	56,248	47,375	1	1	0
New_York_Nor_NY	35621	382	313,377	265,745	0	0	0
New_York_Nor_NY	35622	767	313,806	267,558	0	0	0
New_London_N_CT	35980	50	17,656	15,257	1	1	0
Oklahoma_Cit_OK	36420	189	90,248	71,557	1	1	0
Omaha_NE	36540	203	71,250	60,006	1	1	0
Orlando_FL	36740	206	327,104	244,607	1	1	0
Ventura_Oxna_CA	37100	78	48,050	39,679	1	1	0
Melbourne_Ti_FL	37340	54	77,819	62,289	1	1	0
Panama_City_FL	37460	20	27,381	22,173	1	1	0
Pensacola_FL	37860	46	52,746	43,591	0	1	0
Philadelphia_PA	37980	702	421,831	356,086	1	1	0
Phoenix_AZ	38060	290	681,128	504,978	0	0	1
Pittsburgh_B_PA	38300	270	130,265	112,393	1	1	0
Portland_Van_OR	38900	330	188,543	154,991	1	1	0
Poughkeepsie_NY	39100	107	37,255	32,401	1	1	0
Providence_F_RI	39300	267	102,741	79,664	1	1	0
Raleigh_Durh_NC	39580	139	126,500	105,933	0	1	0
Reno_NV	39900	65	48,611	39,745	1	1	0
Richmond_Pet_VA	40060	116	77,473	62,809	1	1	0
Riverside_Sa_CA	40140	482	439,368	342,387	1	1	0
Rochester_NY	40380	112	29,406	27,503	1	1	0
Sacramento_CA	40900	217	181,888	146,724	1	1	0
St_Louis_MO	41180	350	170,379	136,582	1	1	0
Salem_OR	41420	72	31,185	25,236	1	1	0
San_Diego_CA	41740	206	146,777	123,301	1	1	0
San_Francisc_CA	41860	413	255,945	211,413	1	1	0
San_Jose_CA	41940	78	88,894	74,446	1	1	0
Seattle_Ever_WA	42660	537	262,057	224,584	1	1	0
Springfield__MA	44140	119	44,376	35,486	1	1	0
Stockton_CA	44700	114	60,608	47,784	1	1	0
Tampa_St_Pe_FL	45300	250	386,782	305,187	0	1	0
Toledo_OH	45780	105	45,112	35,671	1	1	0
Tucson_AZ	46060	129	109,998	88,391	0	1	1
Tulsa_OK	46140	132	74,346	59,120	0	1	0
Norfolk_VA_B_VA	47260	84	53,115	43,691	1	1	0
Washington_DC	47900	743	487,432	390,087	1	1	0
Wilmington_NC	48900	39	43,061	35,982	1	1	0
Winston_Salem_NC	49180	62	37,056	31,377	1	1	0
Worcester_MA	49340	135	53,619	42,269	1	1	0

Table A2: Summary Statistics for First Stage Regression

Name	Price ($)		Price-Replacement ($)		Lot Size (1000sqf)		Living Area (1000 sqf)		Year built	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Akron_OH	141,998	436,856	-35,291	558,182	27.53	142.17	1.95	4.79	1960.9	34.3
Albany_Schen_NY	219,164	772,365	12,997	891,904	58.37	356.37	2.23	8.36	1952.7	42.9
Allentown_Be_PA	229,993	644,014	15,952	858,863	24.16	243.51	2.30	8.44	1953.1	43.9
Atlanta_GA	221,194	990,971	-28,399	1,309,007	54.48	1300.44	2.57	14.11	1984.4	23.5
Augusta_Aike_GA	156,652	355,392	-55,095	677,062	72.33	898.09	2.28	7.00	1984.7	26.2
Austin_TX	265,112	1,081,702	60,633	849,511	26.67	360.22	2.34	9.82	1988.0	20.4
Bakersfield_CA	205,113	160,520	60,076	113,517	21.51	1323.99	1.66	0.68	1982.7	24.7
Baltimore_MD	271,463	812,403	116,847	959,917	44.61	3295.76	1.70	7.16	1960.3	35.4
Bend_OR	281,555	325,270	108,701	338,255	58.87	685.93	1.92	3.30	1993.0	18.0
Birmingham_AL	212,369	301,459	64,696	353,412	33.91	199.22	0.91	1.44	1995.1	14.4
Boston_MA	448,325	2,620,627	221,253	1,183,738	22.07	117.19	1.85	1.57	1948.0	44.7
Boulder_CO	387,741	605,321	212,781	428,610	62.50	1859.68	1.93	5.01	1981.2	22.8
Bridgeport_CT	643,064	1,992,681	406,186	1,384,599	26.42	105.42	2.19	1.69	1959.6	35.4
Buffalo_Niag_NY	141,319	4,035,204	-74,274	4,081,852	42.19	251.33	2.31	8.61	1946.5	35.5
Fort_Myers_C_FL	244,528	394,221	87,053	414,006	18.67	120.77	1.77	3.45	1994.6	14.7
Charleston_N_SC	310,780	443,837	140,114	484,240	15.47	425.39	1.92	3.95	1987.6	27.1
Charlotte_Ga_NC	231,927	804,043	1,320	758,749	43.87	285.01	2.47	9.65	1989.6	22.6
Chattanooga_TN	167,640	664,366	-70,264	883,334	58.21	721.16	2.53	7.29	1973.9	28.3
Chicago_Gary_IL	286,058	1,348,522	-279,177	11,000,000	5.95	11.20	5.28	101.82	1943.2	39.5
Chicago_Gary_IL	281,861	899,714	88,894	761,730	9.88	190.48	1.88	7.72	1979.5	25.9
Chico_CA	252,543	237,999			49.69	287.13	1.76	2.55	1977.9	24.3
Cincinnati_OH	168,001	901,948	-16,309	917,434	24.79	159.03	1.97	4.04	1962.6	36.5
Cleveland_OH	148,672	835,774	-25,117	833,855	33.73	149.50	1.90	3.58	1955.7	34.0
Colorado_Spr_CO	239,888	597,171	41,160	987,612	45.38	358.12	2.15	12.05	1985.1	24.0
Columbia_SC	159,021	833,106	-354,985	2,496,838	41.10	568.33	5.09	22.78	1986.7	21.9
Columbus_OH	170,892	411,163	-15,266	935,847	32.34	527.11	2.03	10.25	1972.4	32.1
Corvallis_OR	271,186	252,440			29.56	176.84	2.11	3.86	1977.3	26.3
Dallas_Fort__TX	248,799	2,334,984	5,448	2,176,910	16.64	94.86	2.71	11.18	1994.5	14.8
Dayton_Sprin_OH	124,396	335,284	-46,051	390,848	31.83	536.65	1.88	3.51	1959.6	30.6
Daytona_Beach_FL	201,147	361,138	45,919	303,991	17.41	155.26	1.62	2.48	1983.6	20.0
Denver_Bould_CO	294,908	5,327,734	112,146	5,292,273	53.83	3000.47	1.99	8.48	1978.3	26.8
Des_Moines_IA	158,857	321,564	647	609,679	29.86	2197.95	1.74	7.32	1972.7	35.3
Detroit_MI	91,312	140,150	-50,243	1,267,705	20.18	1803.19	1.57	11.97	1955.5	25.0
Dover_DE	226,195	368,052	51,777	239,451	44.38	331.21	1.84	0.79	1987.2	29.0
Durham_Chapel_Hill_NC	253,449	1,098,616	-3,223	1,215,950	42.58	195.68	2.68	9.48	1985.3	24.9
Eugene_Sprin_OR	222,072	124,094	89,339	101,850	24.77	147.60	1.55	0.66	1975.0	25.3
Fayetteville_NC	141,643	245,692			32.21	422.00	1.80	4.73	1986.3	19.6
Fresno_CA	240,072	303,593	63,508	613,674	41.47	351.74	1.97	7.00	1970.3	23.0
Gainesville_FL	205,232	689,286			32.16	298.09	1.85	6.31	1985.8	19.7
Grand_Juncti_CO	218,127	209,015	66,118	208,077	111.47	2335.65	1.72	1.92	1984.4	25.8
Grand_Rapids_MI	114,436	92,585	-4,668	87,912	149.19	544.77	1.38	0.55	1961.7	40.4
Greensboro_W_NC	180,093	758,964	-50,603	1,026,179	47.87	263.44	2.43	9.93	1978.6	26.6
Greenville_S_SC	171,563	3,303,747			30.38	406.49	1.80	1.95	1986.1	21.0
Harrisburg_L_PA	165,163	422,281	-7,318	439,415	48.37	554.27	1.86	3.98	1954.9	41.1
Hartford_Bri_CT	271,917	644,360	85,644	468,062	30.78	137.02	1.86	1.74	1961.6	36.8
Huntsville_AL	218,440	1,595,598	58,841	1,617,602	12.19	184.77	1.80	3.66	1987.1	20.5
Jacksonville_FL	219,320	501,065	34,484	733,021	25.65	611.88	2.03	8.20	1987.2	23.2
Knoxville_TN	177,845	561,845	5,416	672,862	94.81	5513.12	1.90	5.20	1976.5	28.3
Lakeland_Win_FL	162,238	217,049	7,185	264,131	19.80	145.26	1.78	2.82	1989.4	20.9
Lancaster_PA	194,302	648,034	20,717	823,233	43.12	276.77	1.90	9.13	1956.6	44.6
Las_Vegas_NV	269,780	814,866	69,472	1,512,064	6.31	23.94	2.16	13.73	1996.0	13.2
Lincoln_NE	156,181	216,543	8,714	329,935	21.55	132.44	1.65	3.55	1972.4	31.7
Little_Rock__AR	162,211	353,935	-30,497	431,500	41.08	3246.97	2.09	5.94	1978.6	24.0
Los_Angeles__CA	605,889	2,384,390	403,624	2,150,966	54.70	2340.33	2.19	7.82	1964.0	26.5
Los_Angeles__CA	601,443	906,258	438,812	690,999	4.57	18.90	1.80	4.68	1968.5	14.7
Manchester_NH	266,205	563,815	65,631	203,736	51.26	192.56	1.93	1.55	1962.8	41.2
Medford_OR	257,823	199,256	102,539	147,306	97.56	3812.55	1.70	0.74	1980.4	27.5
Memphis_TN	152,510	416,016	-43,389	449,289	34.70	437.03	2.11	4.29	1975.0	25.6
Miami_Hialea_FL	322,960	943,365	165,001	995,643	8.83	58.26	1.76	7.75	1983.4	18.7
Milwaukee_WI	170,416	473,392	-25,055	552,427	11.80	66.94	2.11	6.19	1946.5	33.2
Minneapolis__MN	264,316	932,088	76,830	1,674,546	22.09	178.56	1.93	17.44	1973.0	32.9
Mobile_AL	198,077	1,082,471	1,500	1,181,470	2.95	64.97	2.16	6.86	1985.9	19.9
Myrtle_Beach_SC	243,219	5,867,544			67.67	3327.69	1.44	2.15	1994.9	14.3
Naples_FL	464,223	936,726			13.99	264.45	1.18	4.17	1994.1	12.4
Nashville_TN	213,281	780,594	4,321	1,096,215	108.67	2539.19	2.26	10.10	1984.7	25.2
New_Haven_CT	258,506	480,046	81,912	291,254	18.80	57.04	1.83	1.55	1955.6	36.8
New_York_Nor_NY	871,137	12,400,000	550,205	8,714,088	12.32	387.65	2.75	29.81	1951.9	33.4
New_York_Nor_NY	444,573	2,459,695	252,808	2,553,680	316.94	14503.39	1.86	7.15	1961.5	32.9
New_London_N_CT	280,921	804,757	108,088	256,496	49.14	181.13	1.77	1.30	1959.1	45.0
Oklahoma_Cit_OK	166,159	1,597,729	-49,200	1,676,793	27.63	192.11	2.31	9.08	1975.3	26.0
Omaha_NE	172,691	511,395	-7,611	1,418,724	48.68	5140.29	1.88	13.05	1971.7	34.3
Orlando_FL	241,365	663,995	49,824	1,677,583	13.28	451.34	2.11	15.78	1991.4	17.4
Ventura_Oxna_CA	552,810	593,305	375,916	465,670	12.87	46.82	1.90	2.18	1979.4	19.0
Melbourne_Ti_FL	199,978	310,715	41,552	347,603	12.82	69.00	1.80	4.01	1987.6	16.9
Panama_City_FL	244,375	349,629	98,553	402,447	41.66	348.85	1.67	3.10	1990.1	18.4
Pensacola_FL	183,144	266,606	10,064	1,005,902	40.29	393.75	1.92	10.23	1985.5	21.5
Philadelphia_PA	238,451	686,074	63,061	571,338	58.28	4167.33	1.88	6.10	1955.4	36.0
Phoenix_AZ	259,351	946,653	47,810	929,747	11.31	120.42	2.28	8.63	1991.6	16.8
Pittsburgh_B_PA	135,652	199,214	-20,648	167,829	30.12	444.07	1.72	1.58	1948.4	35.1
Portland_Van_OR	299,076	879,840	128,664	912,584	33.41	1222.46	1.87	5.59	1975.6	30.1
Poughkeepsie_NY	306,779	430,053	115,281	461,382	72.00	372.06	2.08	4.97	1962.3	40.8
Providence_F_RI	266,099	458,550	81,301	287,559	22.62	103.57	1.88	1.64	1949.7	40.6
Raleigh_Durh_NC	243,361	753,292	15,324	697,414	32.40	607.17	2.44	9.22	1994.0	18.9
Reno_NV	327,093	665,746	132,156	570,594	22.86	287.13	2.13	6.23	1989.5	18.6

Richmond_Pet_VA	272,001	676,070	61,130	536,753	95.12	9676.82	2.21	6.28	1987.0	20.5
Riverside_Sa_CA	315,450	390,663	133,501	399,738	15.50	102.35	2.00	4.85	1987.3	20.6
Rochester_NY	134,156	203,894	-73,680	2,781,475	50.02	350.83	2.13	25.29	1952.0	36.9
Sacramento_CA	329,363	1,278,423	168,694	1,248,819	74.65	5086.70	1.81	3.06	1984.1	21.4
St_Louis_MO	179,025	1,742,242	10,909	1,815,233	17.45	131.22	1.83	7.91	1960.5	32.5
Salem_OR	208,004	225,504	44,469	234,224	39.92	319.91	1.84	2.75	1976.6	27.7
San_Diego_CA	521,052	1,159,567	349,838	940,298	25.04	110.95	1.89	3.73	1975.6	18.4
San_Francisc_CA	660,193	1,555,332	463,706	2,462,976	17.36	661.15	2.09	22.13	1966.4	29.7
San_Jose_CA	707,864	1,062,623	522,666	734,247	8.38	34.30	1.98	6.01	1974.3	22.6
Seattle_Ever_WA	409,663	1,127,689	217,028	1,024,536	48.11	236.03	2.08	9.25	1978.5	28.2
Springfield__MA	203,350	357,377			40.11	203.36	1.86	1.84	1947.3	40.1
Stockton_CA	279,874	190,991	113,766	219,538	13.07	89.24	1.87	1.72	1983.7	25.1
Tampa_St_Pe_FL	216,168	672,392	51,397	563,533	48.54	4420.26	1.85	7.65	1982.5	21.1
Toledo_OH	114,422	205,698	-73,895	921,709	24.32	218.60	2.04	9.28	1950.1	35.0
Tucson_AZ	231,839	456,469	64,801	462,062	11.19	102.21	1.85	5.92	1988.0	18.8
Tulsa_OK	160,765	1,714,034	-46,017	1,775,040	33.52	296.52	2.25	7.77	1973.9	24.2
Norfolk_VA_B_VA	263,756	383,574	96,876	457,961	19.04	1635.31	1.87	4.04	1981.0	18.9
Washington_DC	448,090	1,939,030	260,121	1,538,170	26.97	358.38	2.00	8.76	1979.3	26.3
Wilmington_NC	260,994	338,559	87,052	461,111	26.08	958.26	1.94	4.23	1991.5	21.0
Winston_Salem_NC	172,014	433,461	-35,024	992,465	37.92	226.82	2.24	10.80	1981.5	26.6
Worcester_MA	278,707	1,533,782	79,086	1,270,436	42.91	189.60	1.92	1.63	1953.6	45.6

Table A3: Summary Statistics for Second Stage Regression

Name	Zoning/Regulation Index	Math Scores Mean	Math Scores SD	CERCLA Sites Mean	CERCLA Sites SD	Particulate Matter Mean	Particulate Matter SD	Employment Access Mean	Employment Access SD
Akron_OH	-0.06	-0.04	0.95	0.02	0.14	11.63	0.24	36,859	9,671
Albany_Schen_NY	-0.13	0.19	0.70	0.09	0.29	7.34	0.20	33,418	14,465
Allentown_Be_PA	-0.09	0.39	0.63	0.15	0.37	9.05	0.67	35,570	12,771
Atlanta_GA	-0.14	0.30	0.83	0.00	0.00	11.62	0.17	113,411	50,194
Augusta_Aike_GA	-1.18	0.25	0.83	0.06	0.27	11.25	0.34	17,391	6,957
Austin_TX	-0.08	0.56	0.52	0.00	0.00	9.58	0.26	66,423	28,457
Bakersfield_CA	0.12	-0.09	0.55	0.01	0.12	19.30	2.73	15,685	8,884
Baltimore_MD	0.88	0.29	0.73	0.13	0.35	10.55	0.43	92,794	38,078
Bend_OR		0.80	0.31	0.00	0.00	6.44	0.52	5,830	2,582
Birmingham_AL	-0.24	0.58	0.41	0.00	0.05	10.06	0.06	32,781	11,804
Boston_MA	1.36	-0.11	0.85	0.15	0.39	8.80	0.70	66,996	35,871
Boulder_CO		0.58	0.36	0.00	0.07	6.94	0.26	22,793	6,351
Bridgeport_CT	0.29	0.19	0.77	0.09	0.28	9.22	0.16	42,877	12,618
Buffalo_Niag_NY	-0.54	0.14	1.03	0.11	0.41	9.26	0.17	54,186	20,211
Fort_Myers_C_FL	-0.34	0.53	0.41	0.00	0.00	6.50	0.03	20,193	6,716
Charleston_N_SC	-1.00	0.59	0.72	0.03	0.19	9.01	0.09	25,762	10,086
Charlotte_Ga_NC	-0.60	0.38	0.76	0.03	0.20	10.21	0.06	61,163	23,953
Chattanooga_TN	-0.90	0.41	0.97	0.10	0.30	10.32	0.26	26,903	10,858
Chicago_Gary_IL	-0.12	-0.15	0.69	0.00	0.06	11.46	0.65	261,817	76,115
Chicago_Gary_IL	-0.12	0.59	0.44	0.09	0.42	10.14	0.64	163,687	49,319
Chico_CA	0.72	-0.15	0.56	0.09	0.42	9.16	0.93	7,078	4,740
Cincinnati_OH	-0.74	0.06	1.09	0.09	0.30	12.47	0.63	78,804	28,518
Cleveland_OH	-0.33	-0.08	1.11	0.01	0.12	11.45	0.78	71,135	25,593
Colorado_Spr_CO	0.49	0.63	0.28	0.00	0.00	5.25	0.17	29,986	12,575
Columbia_SC	-0.89	0.50	0.65	0.03	0.21	10.38	0.19	26,078	10,916
Columbus_OH	0.01	-0.06	0.99	0.01	0.09	11.14	0.11	70,275	26,024
Corvallis_OR		0.79	0.46	0.01	0.10	7.64	0.01	6,625	3,536
Dallas_Fort__TX	-0.52	0.72	0.42	0.00	0.07	9.53	0.03	133,830	34,747
Dayton_Sprin_OH	-0.69	-0.29	1.16	0.20	0.46	12.16	0.14	39,622	10,689
Daytona_Beach_FL		0.39	0.45	0.01	0.11	7.10	0.02	13,580	6,178
Denver_Bould_CO	0.68	0.39	0.53	0.08	0.35	7.12	0.71	97,921	37,345
Des_Moines_IA	-1.01	-0.10	1.25	0.10	0.30	9.20	0.03	37,831	12,727
Detroit_MI	-0.08	0.37	0.66	0.07	0.27	10.40	0.46	46,155	19,353
Dover_DE	0.44	0.58	0.52	0.44	0.57	9.45	0.10	6,385	2,404
Durham_Chapel_Hill_NC		-0.14	0.83	0.00	0.05	9.26	0.27	27,918	10,345
Eugene_Sprin_OR	0.17	0.45	0.45	0.00	0.01	7.77	0.46	16,593	9,651
Fayetteville_NC	-0.82	0.02	0.64	0.09	0.29	9.54	0.07	17,313	5,133
Fresno_CA	0.83	0.37	0.74	0.08	0.27	16.69	0.67	34,472	14,005
Gainesville_FL	-0.12	0.51	0.68	0.12	0.32	7.06	0.07	15,356	5,666
Grand_Juncti_CO		0.38	0.38	0.00	0.00	9.49	0.19	9,600	5,369
Grand_Rapids_MI	-0.31	0.75	0.21	0.00	0.02	9.91	0.13	14,238	3,376
Greensboro_W_NC	-0.60	0.25	0.65	0.00	0.00	9.32	0.28	32,735	12,251
Greenville_S_SC		0.70	0.41	0.14	0.38	10.33	0.26	30,789	12,313
Harrisburg_L_PA	0.35	-0.05	1.13	0.05	0.21	12.07	0.12	33,527	13,005
Hartford_Bri_CT	0.32	0.20	0.83	0.06	0.28	8.63	0.30	46,724	17,199
Huntsville_AL	-1.45	0.35	0.86	0.00	0.00	9.95	0.03	23,249	10,006
Jacksonville_FL	-0.16	0.55	0.63	0.07	0.27	7.85	0.13	39,245	15,864
Knoxville_TN	-0.60	0.50	0.80	0.02	0.12	9.04	0.12	30,382	9,977
Lakeland_Win_FL	0.04	0.07	0.45	0.06	0.24	7.23	0.14	14,045	6,436
Lancaster_PA	0.14	0.31	0.61	0.06	0.24	11.79	0.29	26,671	11,791
Las_Vegas_NV	-0.85	0.27	0.64	0.00	0.00	7.56	0.35	88,447	37,709
Lincoln_NE	0.59	0.74	0.29	0.02	0.13	8.12	0.10	29,347	8,062
Little_Rock__AR	-1.05	-0.05	1.02	0.06	0.31	11.03	0.29	33,381	13,974
Los_Angeles__CA	0.34	0.53	0.74	0.12	0.41	14.21	2.32	244,428	85,658
Los_Angeles__CA	0.34	0.81	0.63	0.04	0.20	12.09	1.45	115,095	36,440
Manchester_NH	1.45	0.26	0.55	0.21	0.44	8.19	0.26	25,956	10,637
Medford_OR	0.66	0.32	0.53	0.00	0.00	8.80	1.03	9,053	4,472
Memphis_TN	0.96	-0.05	1.13	0.09	0.34	9.78	0.02	52,887	17,748
Miami_Hialea_FL	0.59	0.44	0.60	0.16	0.47	6.58	0.40	120,643	34,011
Milwaukee_WI	0.10			0.07	0.28	11.49	0.26	94,478	26,868
Minneapolis__MN	0.15	0.70	0.66	0.24	0.64	9.79	0.32	113,331	50,100
Mobile_AL	-1.31	0.75	0.57	0.02	0.15	9.44	0.06	19,333	7,537
Myrtle_Beach_SC	-0.94	0.75	0.34	0.00	0.00	9.62	0.07	12,608	5,242
Naples_FL		0.53	0.49	0.00	0.00	6.41	0.04	17,317	7,386
Nashville_TN	-0.59	0.43	0.98	0.00	0.03	10.21	0.34	46,819	24,229
New_Haven_CT		0.10	0.77	0.15	0.42	9.35	0.33	36,603	10,583
New_York_Nor_NY	0.47	0.57	0.52	0.27	0.60	9.84	0.82	80,401	27,765
New_York_Nor_NY	0.47	0.30	0.79	0.36	0.75	9.04	0.88	70,468	33,397
New_London_N_CT	0.11	0.18	0.71	0.02	0.15	8.16	0.38	13,164	5,883
Oklahoma_Cit_OK	-0.58	0.32	0.96	0.06	0.34	9.15	0.13	51,999	18,093
Omaha_NE	-0.68	0.39	0.63	0.04	0.19	9.12	0.32	53,282	18,324
Orlando_FL	0.20	0.45	0.56	0.04	0.20	7.04	0.04	69,666	26,391
Ventura_Oxna_CA		0.73	0.66	0.06	0.24	10.24	0.13	31,577	8,118
Melbourne_Ti_FL	0.32	0.63	0.51	0.04	0.20	7.15	0.09	16,525	6,421
Panama_City_FL		0.55	0.41	0.00	0.02	9.04	0.09	8,555	4,603
Pensacola_FL	-1.04	0.51	0.63	0.15	0.44	8.81	0.08	14,167	8,183
Philadelphia_PA	0.84	0.17	0.95	0.34	0.67	10.49	0.52	159,978	66,719
Phoenix_AZ	0.53	0.68	0.65	0.02	0.15	8.90	1.53	92,747	41,071
Pittsburgh_B_PA	-0.12	0.38	0.83	0.03	0.20	12.70	0.69	84,893	34,777
Portland_Van_OR	0.12	0.53	0.60	0.16	0.52	7.83	0.28	81,472	33,023
Poughkeepsie_NY		0.20	0.63	0.12	0.33	8.07	0.37	4	348
Providence_F_RI	1.54	0.19	0.82	0.16	0.45	8.06	0.42	53,510	22,724
Raleigh_Durh_NC	0.42	0.45	0.52	0.05	0.21	9.06	0.16	42,091	14,916
Reno_NV	-0.35	0.72	0.62	0.00	0.00	7.63	0.30	25,079	10,785

Richmond_Pet_VA	-0.55	0.50	0.49	0.06	0.25	9.05	0.10	45,864	16,238
Riverside_Sa_CA	0.41	0.45	0.63	0.03	0.18	11.28	3.88	46,052	20,350
Rochester_NY	-0.46	0.12	0.79	0.00	0.02	7.80	0.18	48,201	21,674
Sacramento_CA	0.29	0.43	0.63	0.03	0.18	9.49	0.87	55,143	20,948
St_Louis_MO	-0.90	-0.12	1.19	0.05	0.25	11.29	0.29	90,777	34,568
Salem_OR	0.17	0.32	0.56	0.00	0.02	7.74	0.17	16,269	8,834
San_Diego_CA	0.33	0.83	0.74	0.00	0.00	10.74	1.65	95,532	33,316
San_Francisc_CA	0.69	0.45	0.88	0.05	0.25	10.04	0.24	131,680	68,862
San_Jose_CA	0.00	0.51	0.70	0.70	1.75	9.74	1.05	112,811	37,349
Seattle_Ever_WA	0.80	0.61	0.88	0.13	0.43	8.86	0.34	103,848	46,399
Springfield__MA	0.46	-0.62	0.84	0.01	0.10	8.86	0.25	27,525	11,836
Stockton_CA	0.34	-0.29	0.61	0.13	0.33	11.39	0.68	20,205	7,267
Tampa_St_Pe_FL	-0.33	0.31	0.62	0.08	0.42	7.63	0.12	67,615	25,458
Toledo_OH	-0.85	0.03	0.89	0.00	0.00	11.23	0.20	35,762	9,272
Tucson_AZ	1.07	0.46	0.78	0.00	0.02	6.17	0.76	34,754	17,248
Tulsa_OK	-1.00	0.24	0.88	0.05	0.24	10.62	0.03	47,355	17,901
Norfolk_VA_B_VA	-0.15	0.09	0.54	0.04	0.20	9.19	0.05	54,093	16,734
Washington_DC	0.19	0.24	0.62	0.04	0.19	9.73	0.33	129,428	72,354
Wilmington_NC	-0.81	0.37	0.52	0.03	0.19	9.31	0.21	12,086	7,872
Winston_Salem_NC		0.37	0.66	0.00	0.05	9.69	0.12	25,105	9,755
Worcester_MA	1.87	-0.28	0.90	0.01	0.12	8.79	0.20	28,088	13,795