Land values can be estimated more accurately than total values

Russell Richie
University of Pennsylvania*

March 5, 2025

Abstract

Land value taxation is favored by economists (Clark Center Forum, 2025), yet rare in practice. This is commonly attributed to land being harder to value than total property values, because unimproved land transacts infrequently in urbanized areas where the vast majority of land value lies. However, the claim that land is hard(er) to value seems to have little theoretical or empirical basis. Here I show with parameter recovery simulations of a simple, banal city that land values can actually be estimated more accurately than total values. I discuss how this model can be extended to more realistic settings.

Keywords: land value, mass appraisal, spatial model, parameter recovery simulation

*Corresponding author: drrichie@sas.upenn.edu

1 Introduction

Economists left, right, and center agree that taxing land more, and buildings less, would promote economic growth (Clark Center Forum, 2025). Yet implementations of so-called Land Value Tax (LVT) are rare. There are various explanations for LVT's rarity, from legal barriers (Coughlan, 1998; Coe, 2009) to political ones (Hughes, Sayce, Shepherd, & Wyatt, 2020; Glaeser, 2013; Dye & England, 2010), but perhaps the most common supposed explanation is that the value of land is difficult to estimate (Mills, 1998), especially relative to the total value of real property (land and improvements fixed to it). Suggestions like these can be found in urban economics and public finance textbooks (Glaeser, 2013; Sieg, 2020), centuries old treatises (Destutt de Tracy, 1817), the blogosphere (Haberkern, 2023), post-mortems of failed LVT reforms (Henry George Foundation of America, 2009), and even an address by the president of Lincoln Land Institute, an LVT advocacy organization (lincoln superuser, 2023). Indeed, the introductory article to the 2022 special issue of the *Journal of Housing Economics* on land valuation claims "[v]aluing urban land is a remarkably vexing problem" (McMillen & Zabel, 2022, p.1).

Yet, as far as we can tell, the claim that land is harder to value than total property mostly goes asserted with little theoretical or empirical basis, or any qualification of when this claim is true or not. Usually, it is justified simply on the basis that land values are directly observed less often than are total values, because vacant properties transact far less often than do improved properties (Cororaton, 2022).

However, it's not difficult to imagine reasons why land values might be easier to estimate than total values, or why the above intuition might be wrong or at least incomplete. For one, the infrequency with which vacant land transacts might not be such a problem, because every improved property sale contains information about land value – two identical buildings sold in two different locations have different prices owing to their land value – and regression techniques can separate contributors to land value from contributors to improved value (Clapp, 2003; Bryan & Sarte, 2009; Kolbe, Schulz, Wersing, & Werwatz, 2012, 2019; Albouy

& Shin, 2022).

Moreover, total values depend on improvements, many of which are inside buildings and difficult for mass appraisers to capture, and since improved values can vary wildly between neighboring parcels, it is not possible to simply interpolate improved values between neighboring parcels. Estimating land values, on the other hand, might not require observation of any of the spatial amenities that affect it. If one can get land values from vacant land sales, teardowns, paired sales analysis, or sophisticated regression techniques thereof (Kolbe et al., 2012, 2019; Albouy & Shin, 2022), then simply interpolating between these (indirectly) observed land values might be sufficient, owing to the high spatial auto-correlation between land values.

Indeed, some professional appraisers and economists seem to share these intuitions. Doucet, Alexander, and Smith (2022) reports that one prominent assessor, Ted Gwartney, claims:

> "**[I]t's easier to assess land than buildings**, because in most cases, the **value of land is derived almost entirely from the location**. Land doesn't have as many fiddly variables, like how much damage your roof took from the last hailstorm and whether you've remodeled your bathroom in the past five years." [emphasis mine]

Similarly, Dwyer (2014, p. 274) claims:

> "In comparison with the mass appraisal of heterogeneous improved parcels under a system that taxes both buildings and land, the mass appraisal of land values alone is much easier. **The continuity of value per square foot enables checking and extrapolation of bare land values (obtained from demolition purchases) over several parcels.** This is not valid for property taxes on buildings. The administrative superiority of land value taxation over property taxation (of land and buildings together) is evidence by the ability of the New

> South Wales Valuer-General to revalue the Sydney metropolitan area every two years instead of every six, once he was relieve of the necessity to give valuations of improvements (Hutchinson, 1981, p. 274)" [emphasis mine]

Similar sentiments can be found in the 1990 open letter to USSR President Mikhail Gorbachev (Fitzgerald, 1990), signed by 30 economists and other academics, including three Nobel Prize winners. The letter advocated for land value taxation, arguing "The assessment process is simplified by the fact that land rental values tend to change smoothly with location".

All of these arguments are consistent with the idea that land valuation could, at least in some cases, be easier than property valuation because of the greater spatial auto-correlation among land values than among improved values, and (in Gwartney's case) the difficulty in observing some improvements and the non-necessity of observing location amenities. Neighboring parcels will have nearly identical land value per square foot, even if one is vacant and the other has a skyscraper, so it is easy to interpolate unobserved land values from observed ones (whether through vacant land sales, teardowns, or other means).

Overall, then, while conventional wisdom seems to claim that land valuation is more difficult than total property valuation, there are reasons to think this is not always the case. Of course, the valuation accuracy of land compared to improvements or total value could depend on all of the above factors: how frequently unimproved land transacts, the spatial auto-correlation of land, the observation of improvements, or other factors yet not mentioned. But with only intuitive, purely verbal models, it is difficult or impossible to know how these factors collectively determine relative valuation accuracy.

To address this, we have constructed a simple stochastic model of a city and property transactions therein. In this model, 'true' land and total values are known and are the basis of sales prices, and standard land and property valuation methods can be applied to these sales to attempt to recover the true land and property values.

In what follows, we describe our model in more detail, our simulation results, and discussion of our results. To preview, we find that it is indeed possible to construct a fairly banal city in which land values can be estimated more accurately than total property values.

2 Method

Code for our city and appraisal models can be found here.

2.1 City model

In our model, parcels lie on a square grid of size (M, M), and are all the same size. This latter simplifying assumption allows us to abstract from parcel size entirely, and assume that a parcel's land value depends only on its location. Following the standard monocentric city model, the land values for each of the parcels (x, y) are based on an exponential decay of their Euclidean distance from the city center (x_c, y_c), with the distances subject to a small amount of normally distributed, 0-mean noise:

$$d(x, y) = \sqrt{(x - x_c)^2 + (y - y_c)^2} \tag{1}$$

$$d_{noisy}(x, y) \sim \mathcal{N}(d(x, y), \sigma_{lv}) \tag{2}$$

$$lv_{true}(x, y) = lv_{center} \cdot \exp\left(-\lambda \cdot d_{noisy}(x, y)\right) \tag{3}$$

where lv_{center} is the land value in the center of the city, λ is a parameter controlling the decay rate, and σ_{lv} is a parameter controlling the spatial autocorrelation of land values, such that when σ_{lv} increases, the spatial autocorrelation decreases. Adding normally distributed noise to the distances and not directly to the land values has two effects. First, we guarantee that all land values are positive. While negative land *prices* are theoretically possible if holding costs like taxes exceed land rents (i.e., if the land is over-assessed and/or the land tax rate exceeds the capitalization rate), land values should always be strictly non-negative as land rents can not be less than 0. The second effect is that local idiosyncracies in land value will be of greater absolute magnitude toward the center of the city. This can arise if, for example, one parcel close to the urban core is zoned much more liberally than one right next to it (as happens with highly localized zoning overlays in cities like Philadelphia). Such differences in zoning will have less effect in the city periphery where land values are not very high even under liberal land use rules.

Improvements are captured by a single variable, isq_{true}. For convenience, we refer to this as improved square footage, but it can also be viewed as a composite variable of many improvements, including not only improved square footage, but also building condition, age, number of rooms, etc. We assume that the magnitude of this improvement variable, isq_{true}, is proportional to lv_{true}, under the assumption that building density – or the magnitude of some composite variable of improvements – is highest in places with high land values (building density is generally how high land demand is accommodated). Similar to land values, noise is also added to isq_{true}, with standard deviation proportional to lv_{true}, so that

$$isq_{true}(x, y) \sim \mathcal{N}\left(lv_{true}(x, y), lv_{true}(x, y) \cdot \sigma_{isq}\right) \tag{4}$$

where σ_{isq} is a parameter controlling the correlation of improved square footage with land values, but also spatial auto-correlation of improvements; as σ_{isq} increases, land values and square footage become less correlated, and improved square footage varies less smoothly over space. Since isq_{true} depends on lv_{true}, when $\sigma_{isq} > 0$ the spatial auto-correlation of isq_{true} will tend to be lower than that of lv_{true}. We also clip negative values of isq_{true} to 0, under the assumption that a parcel can not have fewer than 0 improved square feet (although this constraint becomes less important if one instead views isq_{true} as a composite variable of arbitrary scale and range). Finally, note that Equation 4 assumes that variation in isq_{true} is larger in places of large lv_{true}. This captures the fact that a city center, with high land values, will have large variations from parcel to parcel in improvements – a skyscraper next to a vacant lot – while in a city periphery, usually at most a detached single family home will abut a vacant lot.

Improved values are a noisy linear function of improved square footage:

$$iv_{isq}(x, y) = p_{isq} \cdot isq_{true}(x, y) \tag{5}$$

$$iv_{true}(x, y) \sim \mathcal{N}\left(iv_{isq}(x, y), iv_{isq}(x, y) \cdot \sigma_{iv}\right) \tag{6}$$

where p_{isq} is the price per improved square foot (or per unit of isq_{true} if one views it as a composite variable), and σ_{iv} controls the importance of improved variables (condition, age, number of rooms, etc.) that impact improved values but are unobserved (as some improved variables inevitably will be). As σ_{iv} increases, improved values become less predictable from isq_{true}. Note again that the scale of noise in true improved values depends on the improved values from square footage. This captures the assumption that smaller observed improvements will tend to have smaller variations in unseen improvements. For example, the impact of interior building quality, often difficult to capture in mass appraisal, will be much greater (potentially on the scale of millions of dollars) for large buildings than for small buildings.

Improved values are clipped at 0 [1]; such cases are effectively vacant lots with no improvements. However, as will become apparent when we describe our mass appraisal model, we do not exploit such cases as vacant land transactions when valuing land. Arguably, exploiting these as vacant land sales would make estimation of land values even easier.

True total values are just land values plus improved values:

$$tv_{true}(x, y) = lv_{true}(x, y) + iv_{true}(x, y) \tag{7}$$

Last, we assume that only some subset of properties transact during the assessment period. We currently assume that these include every property whose indices (x, y) are both divisible by N_{train}. For these transacted properties, observed total values are obtained

[1] Negative improved values are possible when a building is totally uninhabitable, requiring teardown before the land can be (re)improved. Such cases are fairly rare. Our model could be modified to allow negative improved values.

from true total values with noise added, reflecting typically unobserved idiosyncrasies of the transaction like buyer and seller characteristics:

$$tv_{observed}(x,y) \sim \mathcal{N}\left(tv_{true}(x,y), tv_{true}(x,y) \cdot \sigma_{tv}\right) \tag{8}$$

where σ_{tv} controls, for example, how imbalanced the negotiation skills of buyer and seller are. When σ_{tv} is high, then buyers (sellers) are able to negotiate much lower (higher) sale prices than would be expected from the "true" price of properties.

2.2 Mass appraisal

Our mass appraisal model starts with the very common assumption – and indeed one we made in Equation 7 – that improved property values are an additive function of an improved component, and a location component. We also assume, as is common and as embodied in Equation 5, that improved values are a linear function of improved characteristics. Thus, we wish to estimate the equation:

$$tv_{observed}(x,y) = \hat{\beta} \cdot X(x,y) + \hat{L}(x,y) \tag{9}$$

where $\hat{\beta}$ represents the estimate of effects of improved characteristics in X, and $\hat{L}$ is the estimate of a function of land value based on location [2]. While some mass appraisers take the approach of modeling $\hat{L}$ with many locational attributes like distance to the central business district and other (dis)amenities, we will instead model $\hat{L}$ non-parametrically. Our problem, therefore, is to estimate the parametric component, $\hat{\beta}$, and the non-parametric component, $\hat{L}$, in an efficient, unbiased manner. To do so, we use a two-stage semi-parametric approach described in Bryan and Sarte (2009), Kolbe et al. (2012), Kolbe et al. (2019), and others.

[2]Note we do not estimate a fixed (building) intercept. The two-stage semi-parametric approach is unable by itself to allocate value to the fixed intercept and to the location component, but if one wished to do so, one could, as Kolbe et al. (2019) explain, anchor residualized land values to a vacant land sale.

2.2.1 Stage one: Estimating improvement effects

In the first stage, we use the semiparametric estimator of Yatchew (1997) and Wang, Brown, and Cai (2011) to split transacted properties' prices into the improved and land components. The key idea of this estimator is that the location variable, $\hat{L}$, can be ignored when comparing prices of nearby properties. This requires that sales data are ordered to be geographically close to each other. In other words, the Traveling Salesman Problem must be solved – or more practically for the size of typical assessment datasets, approximated – for the transacted properties. We follow Yatchew (1997) and order the observations along a path created from the greedy nearest-neighbor algorithm, which visits cities one by one by starting from a seed city, and subsequently visits the nearest unvisited city until all cities have been visited. We then calculate the difference between two nearby observations, i and $i-1$:

$$\begin{aligned} tv_{observed}(x_i, y_i) - tv_{observed}(x_{i-1}, y_{i-1}) = {} & \hat{\beta} \cdot [X(x_i, y_i) - X(x_{i-1}, y_{i-1})] \\ & + L(x_i, y_i) - L(x_{i-1}, y_{i-1}) \\ & + \epsilon_i - \epsilon_{i-1} \end{aligned} \tag{10}$$

Since i and $i-1$ are nearby, then $L(x_i, y_i) - L(x_{i-1}, y_{i-1})$ should be negligible, as long as the location value function is smooth enough. The remaining $\hat{\beta}$ can then be estimated with ordinary least squares.

2.2.2 Stage two: Residualizing and interpolating land values

In the second stage, we (1) estimate residual land prices for transacted properties, and (2) use these residual land prices to interpolate land prices for non-transacted properties. (1) is straightforward: the value of the location component for transacted properties can be estimated by subtracting $\hat{\beta} \cdot X(x, y)$ from observed sale prices:

$$\hat{L}(x,y) = tv_{observed}(x,y) - \hat{\beta} \cdot X(x,y) \tag{11}$$

Since observed total values are noisy, this difference will sometimes obtain negative land values; to account for this we simply clip all land values estimated in this way to 0.

For (2), many different interpolation techniques are possible. We only analyze kernel regression, for several reasons. First, we wish to keep our analysis tractable. Second, kernel regression is arguably simpler than other methods like Adaptive Weights Smoothing and kriging. Third, for the parameter setting we describe below, land values interpolated with kernel regression led to the most accurate estimates of land and total values. Fourth, and finally, kernel regression is one of the more common spatial interpolation methods, and indeed was also used in Kolbe et al. (2019) which is the main inspiration for our mass appraisal approach. Future research could of course further explore how choices in interpolation method influence the (relative) recoverability of land and total values.

The essence of kernel regression is that an estimate of $\hat{L}(x,y)$ ought to depend more on nearby land values, $L(x,y)'$, than on distant land values, where 'close by' is determined by some kernel function, $K(\hat{L}(x,y) - L(x,y)')$. For example, Kolbe et al. (2019) used the classic Nadaraya-Watson kernel regression (Nadaraya, 1964; Watson, 1964), also known as 'local constant' regression, which simply estimates a point by a weighted average of known points, where the weights are determined by a kernel function, commonly a Gaussian. Unfortunately, this approach suffers from bias issues at the edge of support. For example, if the true function is decreasing towards the edge of support – as a monocentric city's land values generally do – then this approach will overestimate land values towards the edges of the city. We therefore utilize an extension known as local linear regression (Li & Racine, 2004), which, instead of computing the weighted average around (x,y), estimates a linear regression around (x,y). Known land values influence the intercept and beta at (x,y) in proportion to their kernel-given proximity to (x,y). We thus estimate $\hat{L}(x,y)$ as follows:

$$\hat{L}(x,y) = e_1^\top \left(X^\top W X\right)^{-1} X^\top W Y \tag{12}$$

where W is the diagonal matrix of kernel weights $K(\hat{L}(x,y) - L(x,y)')$, Y is the response vector containing all observed $L(x,y)$, and $e_1 = (1,0)^\top$ contains the intercept.

To implement this model, we utilized the KernelReg class in the statsmodels library for Python (Seabold & Perktold, 2010), with the default Gaussian kernel function whose bandwidths (in the x and y dimension) were chosen by least-squares cross-validation.

Once land values for non-transacted properties are obtained, total values for these properties were estimated by summing the estimated land values, and the estimated improved values from stage one, according to Equation 9.

Parameter recovery of tv_{true} and lv_{true} was measured by three standard metrics in property assessment (Hand & Vegari, 2019):

- **Median Ratio** is simply the median ratio of assessed to true values. When the ratio is above 1, then properties are systematically overvalued, and when it is below 1, properties are systematically undervalued. The IAAO recommends a level of assessment ratio between 0.90 to 1.10 across all types of properties and markets (International Association of Assessing Officers, 2013).

- **Coefficient of Dispersion (COD)** measures uniformity or accuracy in assessments, and is the mean absolute deviation (as a percent) from the median ratio. A COD between 5 and 15 is recommended by the IAAO for an assessment jurisdiction.

- **Price-related Differential** measures progressivity or equity in assessments, and is the mean ratio divided by the mean ratio weighted by sale price. A PRD less than 1 indicates lower priced homes are under-assessed relative to higher priced homes. Conversely, a PRD greater than 1 indicates lower priced homes tend to be over-assessed. A PRD between 0.98 and 1.03 is recommended by the IAAO.

We calculate each metric only for the properties that did not transact. In an assessment context, of course, assessments are provided for all properties (and arguably the sales price of a transacted property should just be its assessed value), but by limiting our evaluation only to non-transacted properties, our results are more generalizable to settings – not necessarily related to tax assessment, per se – where true out-of-sample predictions must be made (e.g., forecasting future changes in property values).

3 Results

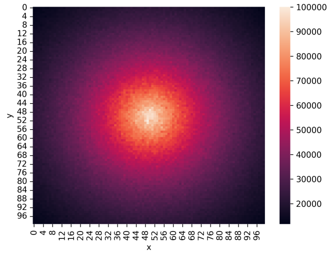
3.1 Realistic simulation conditions

Parameter	**Value**
M (grid size)	100
lv_{center}	\$100000
λ (land value decay rate)	.03
σ_{lv}	1
σ_{isq}	.25
p_{isq}	\$4
σ_{iv}	.15
σ_{tv}	.025
N_{train}	3

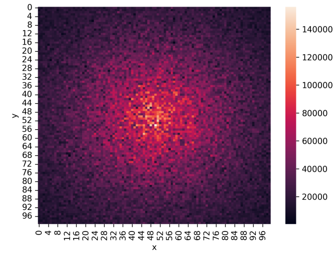
Table 1: Parameters in primary simulations

In our primary simulations, we use the parameters in Table 1, which were chosen to obtain a somewhat prima facie realistic city (in terms of land and total values, the ratio of land to total value) and assessment context, as well as somewhat typical and acceptable assessment metrics according to IAAO. For example, when $N_{train} = 3$, roughly 11% of properties transact, which is a realistic assumption if the assessment period covers a few years, given that 2.5% to 4% of properties in the US transact per year over the last 10 years (Campa, 2024).

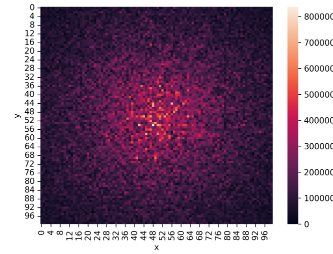
Figure 1 shows one simulation of our city model with these parameters. As can be seen, our model produces a standard mono-centric city model, where land values generally increase



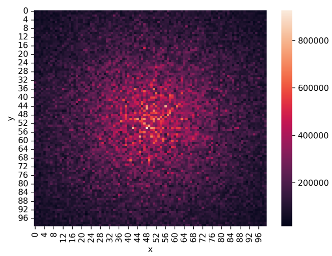
(a)



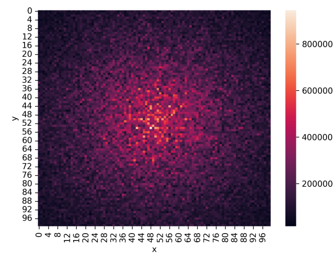
(b)



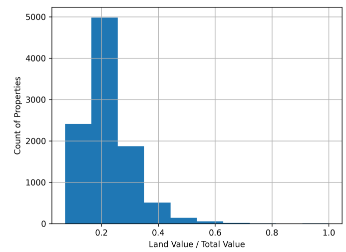
(c)



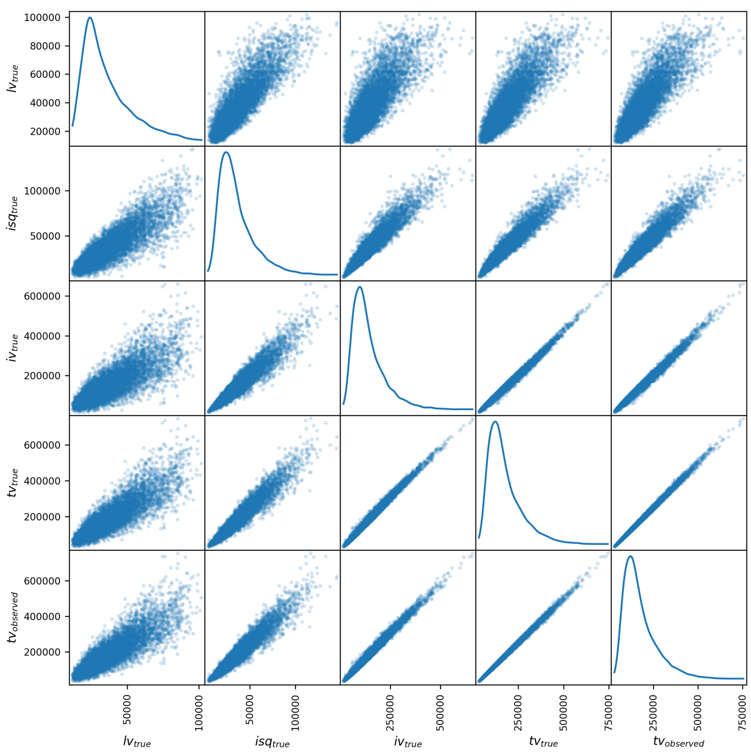
(d)



(e)



(f)



(g)

Figure 1: (a) True Land values, (b) Improved square footages, (c) True improved values, (d) True total values, (e) Observed total values, (f) Ratio of true land value to true total value, and (g) Scatter matrix of key quantities in the city model, in one run of the simulation.

towards a city center, but with small deviations related to inevitable local idiosyncratic spatial (dis)amenities (e.g., distance to parks, schools, crime, pollution, etc.). Improved square footages, improved values, and total values are also higher in the city center, but are generally noisier than land values. The modal ratio of land value to total value is around .2, which resembles conventional wisdom among professional mass appraisers (Philadelphia Office of Property Assessment, 2022).

Figure 2 shows joint density plots of true and predicted land and total values, and Table 2 shows results across 300 simulations. As can be seen, land values are estimated more accurately by COD, and more progressively by PRD, than are total values. However, land values seem to be under-assessed slightly (but within the IAAO's range of acceptable Median Ratios), while total values show no consistent over- or under-assessment. In the discussion, we argue this slight under-assessment of land values is less meaningful.

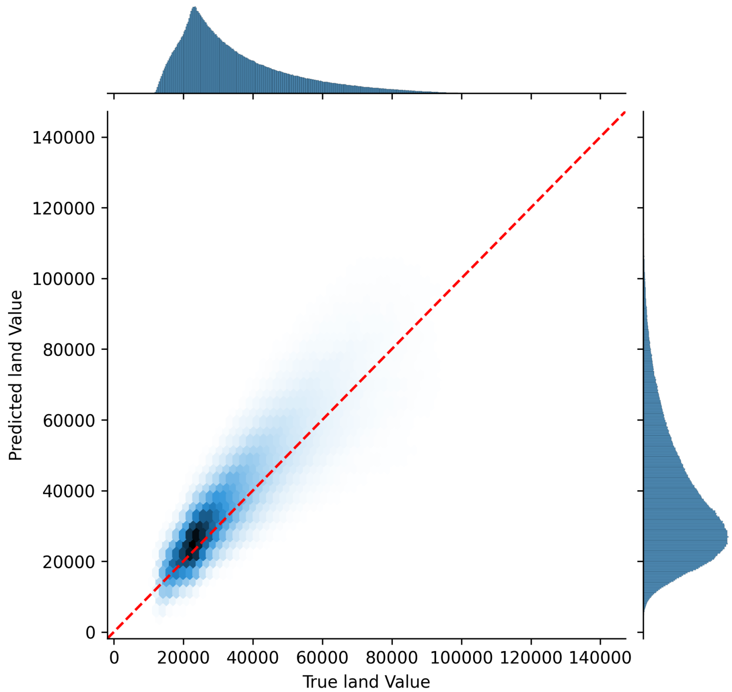
	Median Ratio	Coefficient of Dispersion	Price-Related Differential
Land Value	0.95 (0.94, 0.96)	7.81 (7.64, 7.97)	1.01 (1.01, 1.01)
Total Value	1.00 (1.00, 1.00)	9.92 (9.91, 9.94)	1.02 (1.02, 1.02)

Table 2: Mean (95% CI) of performance metrics under primary simulation conditions in Table 1

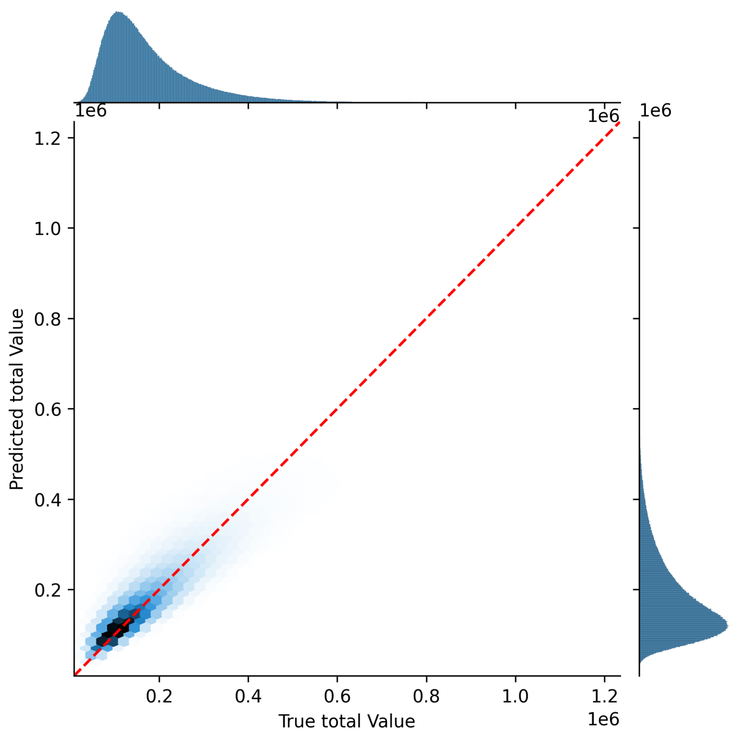
3.2 Parameter sweep

How does this apparent land valuation advantage depend on the parameters of the city model? To better understand this, we simulated the city and appraisal models while varying three noise parameters at two levels each: σ_{lv} (1 vs 10), σ_{isq} (.01 vs .25), and σ_{iv} (.15 vs .3). We skip variation of parameters like N_{train} and σ_{tv} simply for tractability of analysis[3]. We simulated each parameter combination 50 times. Not all of these parameters were designed to be especially realistic (e.g., $\sigma_{isq} = .01$ leads to cities where observed improvements corre-

[3]However, informal experiments suggest that increasing N_{train}, thus decreasing the size of the sales data, hurts land valuation relative to total valuation. The effect of σ_{tv} was more mixed and more difficult to understand.



(a)



(b)

Figure 2: (a) True vs predicted land values, (b) True vs predicted total values across 600 simulations with the parameters in Table 1.

late almost perfectly with land values). Rather, extreme conditions were selected to better illustrate behavior of the model.

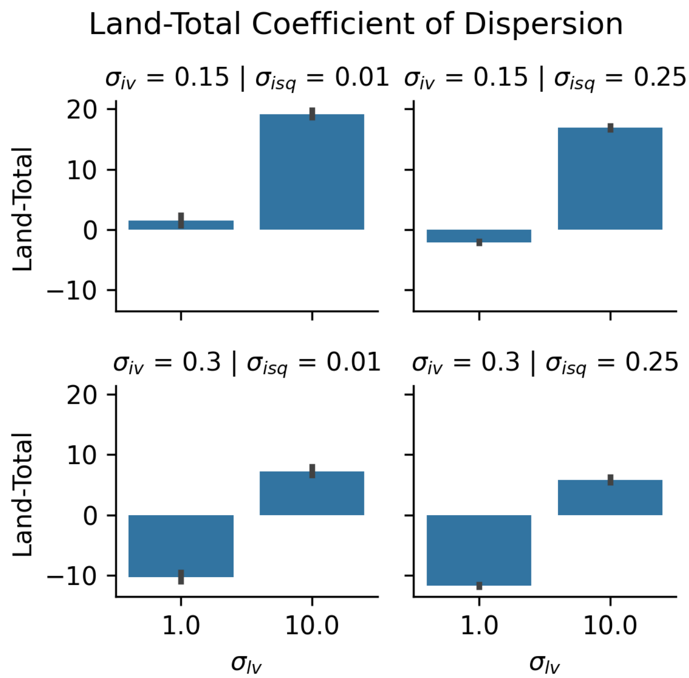
Figure 3 shows the result for all metrics. Generalizing across metrics somewhat:

Decreasing σ_{lv} improves land valuation relative to total valuation. This is because this source of noise obscures both land and total values, but the noise is larger relative to land values than to total values since total value is strictly larger than land value in our model.

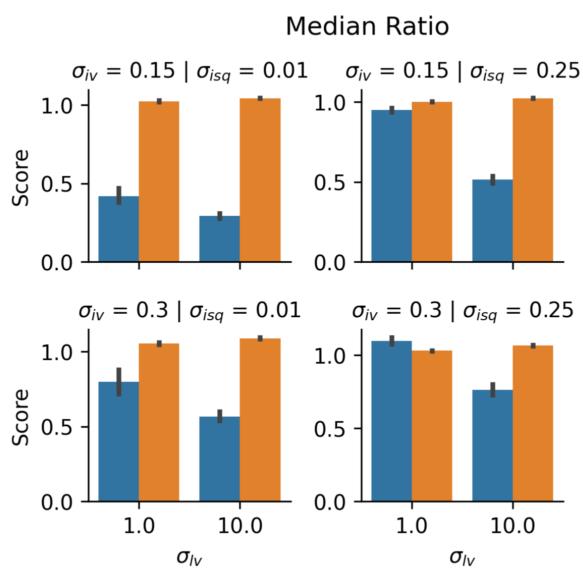
Decreasing σ_{iv} improves total valuation relative to land valuation. This is because when improved value can be estimated perfectly from observed improved characteristics, isq_{true}, then any error in total value is due to error in land value, but this error will be larger relative to land value than to total value, since total value is necessarily larger than land value in our model.

Decreasing σ_{isq} also improves total valuation relative to land valuation, more so in median ratio than COD. This is because (1) decreasing σ_{isq} causes land values and improved square footage to become increasingly collinear, and (2) our two-step appraisal method estimates improved variables' effects first. This allows improved variables to account for all the predictable variance in total values, meaning estimations of land values are increasingly noisy. Of course, this is somewhat idiosyncratic to our two-step approach, and in any case, improved characteristics are not, in the real world, perfectly collinear with land values.

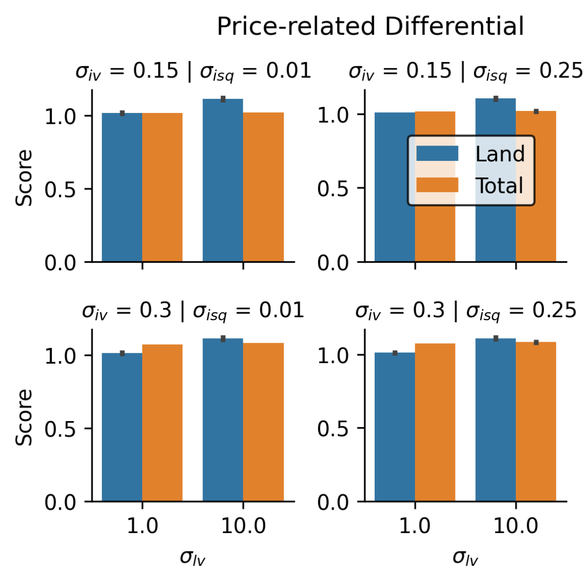
Overall, it can be seen that land can be valued more consistently (by COD) and more progressively (by PRD) than total value when the following are true to some degree: spatial auto-correlation between land values (σ_{lv}) is high, noise in improved values (σ_{iv}) is moderately high, and the correlation between land values and observed characteristics (σ_{isq}) is imperfect.



(a)



(b)



(c)

Figure 3: Results from parameter sweep simulations. Panel (a) displays the difference in Coefficient of Dispersion for land and total valuations (lower indicates better relative performance for land valuations).

4 Discussion

Land value tax is just and efficient (Forrester, 2024), but rare. This rarity is commonly explained with the claim that land value is harder to estimate than overall property value. Yet, as far as we can tell, there is little theoretical or empirical basis for this claim. To address this, we simulated property transactions and mass appraisal of simple monocentric cities. Contrary to popular wisdom, we found that under fairly banal conditions – when land values are spatially auto-correlated, imperfectly correlated with improvements, and some improvements are unobserved – land can actually be valued more accurately than property as a whole by Coefficient of Dispersion, and more progressively by Price-Related Differential. However, we did find that land values are slightly under-assessed while total values showed no consistent over- or under-assessment. We now discuss these findings in more depth.

First, we want to re-emphasize that, while our city model will occasionally generate vacant lots, our mass appraisal model does not exploit them as such. To us, this only further undercuts the claim that the lack of urban vacant land means land is (always) harder to value than total property. That said, future work could explicitly exploit vacant land. As we mentioned earlier, explicitly leveling on vacant lots *as vacant lots* may be necessary, for example, to estimate separate improved and land value intercepts under our two-stage mass appraisal approach. In addition, various techniques have been developed to exploit vacant lot sales alongside improved sales for the purposes of land valuation (Albouy & Shin, 2022), and our work could be extended to such techniques. We caution, however, note that future work ought to consider that, unlike in our city model, real vacant lots tends to be somewhat different from improved properties – vacant lots are often unused for a reason.

Second, while our model's systematic tendency to slightly underestimate land values (and no over/under-assessment in total values) can not be dismissed entirely, we suggest this is less important than the findings with COD and PRD, for two reasons. First, taxpayers generally are not upset by underassessments. Second, many tax jurisdictions adjust the tax rate in response to the assessed values to obtain enough revenue to cover public expenditures. Thus, if land values tended to be under-assessed slightly, policymakers would likely compensate by raising the tax rate slightly.

Third, the possibility that land could in some cases be easier to value than total property leads to a tantalizing possibility: that land value taxation could alleviate one of the greatest complaints with property tax, that property assessments are inaccurate and regressive (Berry, 2021; Ding & Barca, 2022). A shift to land value tax could thus partly assuage the property tax revolts currently roiling the US (Walczak, 2024).

Fourth, recall that our city and appraisal models assumed linear separability of land/location and improvement value. This is a common assumption, but it is probably not true when over large spatial scales (e.g., entire cities). Rather the value of an improvement may vary from location to location within a city. For example, a driveway or garage is less valuable when on-street parking is free and abundant. For this reason, mass appraisal will often develop separate models – and improvement coefficients – for different geographic submarkets. Or one can account for this with geographically weighted regression, which allows the coefficients for improvements (and an intercept for land) to vary over space. Nevertheless, we don't view our assumption as particularly problematic, because one might just view our city and appraisal models not as models of entire *cities*, but of a neighborhood or geographic submarket, within which improved square footage or other observed improvements have constant value.

The last and perhaps most important issue our result will raise is of course whether our city model is sufficiently realistic. This question comes in two forms. First, there is the question of whether we have modeled everything that affects the relative ease of estimating land or total property values. Certainly, there are many aspects of cities we have omitted. For example, we have abstracted away from the fact that parcels vary in size and shape, with parcels growing larger with distance to a city center, and that larger parcels (controlling for location) generally see a discount in land price per square foot (Gilliland & Gunadekar, 2010). Nor do we model temporal dynamics in values and sale prices due to factors like investment, depreciation, or speculation. It is not clear to us that incorporating these elements would eliminate the basic result that there are (ordinary) conditions where land value can be estimated more accurately than overall value, but it may be valuable for future research to expand the realism of the model and test those intuitions.

The more valid question about realism, in our opinion, concerns the parameterization of our city model. As we explained above, we chose our parameter setting to mimic real cities as much as possible in terms of, e.g., their ratio of land to total value. But the realism of some aspects of our model is difficult to know. Is it realistic, for example, that land values auto-correlate at the levels in our simulations? Not having access to true land values, only property sale prices which are noisy, indirect measures of true values, it is difficult to know the answer to this question.

Still, we think our result alone should be enough to move commentators from making simplistic claims like "Land is hard to value" or "Land is harder to value than property" to nuanced claims like "Land is harder to value than total property when land values have low spatial autocorrelation, land and improved characteristics are collinear, all important improvements are observed, etc.". Moreover, economists, policy makers, advocates, and others should consider that valuing land accurately may not be the greatest barrier to land value taxation, and that legal and sociopolitical barriers may need more attention.

5 Acknowledgments

Many thanks to Lars Doucet and Greg Miller of the Center for Land Economics for feedback on this paper. All mistakes are my own.

References

Albouy, D., & Shin, M. (2022, December). A statistical learning approach to land valuation: Optimizing the use of external information. Journal of Housing Economics, 58, 101873. Retrieved 2025-02-17, from https://linkinghub.elsevier.com/retrieve/pii/S1051137722000456 doi: 10.1016/j.jhe.2022.101873

Berry, C. (2021, March). Reassessing the property tax (Tech. Rep.). The University of Chicago, Harris School of Public Policy and the College. Retrieved from https://law.yale.edu/sites/default/files/area/center/corporate/spring2022_paper_berrychristopher_2-24-22.pdf

Bryan, K. A., & Sarte, P.-D. G. (2009). Semiparametric estimation of land price gradients using large data sets. FRB Richmond Economic Quarterly, 95(1), 53–74.

Campa, M. W., Elijah de la. (2024, September). Just 2.5% of U.S. Homes Changed Hands This Year, The Lowest Rate in Decades. Retrieved 2025-02-17, from https://www.redfin.com/news/home-sales-turnover-2024/

Clapp, J. M. (2003). A semiparametric method for valuing residential locations: application to automated valuation. The Journal of Real Estate Finance and Economics, 27, 303–320.

Clark Center Forum. (2025). Land value tax. https://www.kentclarkcenter.org/surveys/land-value-tax/. (Accessed: 2025-02-17)

Coe, R. D. (2009). The legal framework in the united states. In R. F. Dye & R. W. England (Eds.), Land value taxation: Theory, evidence, and practice (pp. 129–170). Cambridge, MA: Lincoln Institute of Land Policy. Retrieved from https://www.lincolninst.edu/app/uploads/legacy-files/pubfiles/land-value-taxation-chp.pdf (Accessed: 2025-02-17)

Cororaton, S. G. (2022, April 19). Land market has its best year in nearly a decade. Retrieved from https://www.nar.realtor/blogs/economists-outlook/land-market-has-its-best-year-in-nearly-a-decade (Accessed: 2025-02-17)

Coughlan, J. A. (1998). Land value taxation and constitutional uniformity. Geo. Mason L. Rev., 7, 261.

Destutt de Tracy, A. L. C. (1817). A treatise on political economy. Trans. by T. Jefferson, Georgetown, 72.

Ding, L., & Barca, A. (2022, May). Can more regular reassessment help improve property tax equity in philadelphia? (Tech. Rep.). Federal Reserve Bank of Philadelphia. Retrieved from https://www.philadelphiafed.org/-/media/FRBP/Assets/Community-Development/Briefs/can-more-regular-reassessment-help-improve-property-tax-equity-in-philadelphia.pdf

Doucet, L. A., Alexander, S., & Smith, N. (2022). Land is a big deal: Why rent is too high, wages too low, and what we can do about it. Shack Simple Press.

Dwyer, T. (2014). Taxation: the lost history. American Journal of Economics and Sociology, 73(4), 664–988.

Dye, R. F., & England, R. W. (2010). Assessing the theory and practice of land value taxation. Lincoln Institute of Land Policy Cambridge, MA.

Fitzgerald, K. (1990). Letter to Gorbachev. Retrieved 2025-02-17, from https://www.prosper.org.au/2007/11/letter-to-gorbachev/

Forrester, P. (2024, June). Henry george: An exploration of some consequences to taxing only land. Library of Economics and Liberty. Retrieved from https://www.econlib.org/library/columns/y2024/forresterpovertysolution.html

Gilliland, C. E., & Gunadekar, A. (2010, January). Small, medium, large: Tract size affects land prices. Tierra Grande. Retrieved from https://trerc.tamu.edu/wp-content/uploads/files/PDFs/Articles/1923.pdf

Glaeser, E. L. (2013). Urban public finance. Handbook of public economics, 5, 195–256.
Haberkern, C. (2023, January). Against Land Value Taxes [Substack newsletter]. Retrieved 2025-02-17, from https://generalwares.substack.com/p/against-land-value-taxes
Hand, N., & Vegari, M. (2019). OPA-analysis/sales_ratio_study.ipynb at master · PhilaController/OPA-analysis. Retrieved 2025-02-17, from https://github.com/PhilaController/OPA-analysis/blob/master/sales_ratio_study.ipynb
Henry George Foundation of America. (2009, April). Summary of land value tax reform efforts in philadelphia, pa: 1980 to the present. Retrieved from https://cooperative-individualism.org/henry-george-foundation_summary-of-land-value-tax-reform-efforts-in-philadelphia-2009-apr.pdf (Accessed: 2025-02-17)
Hughes, C., Sayce, S., Shepherd, E., & Wyatt, P. (2020, May). Implementing a land value tax: Considerations on moving from theory to practice. Land Use Policy, 94, 104494. Retrieved 2025-02-17, from https://linkinghub.elsevier.com/retrieve/pii/S0264837719315704 doi: 10.1016/j.landusepol.2020.104494
Hutchinson, A. R. (1981). Land rent as public revenue in australia. Economic and Social Science Research Association.
International Association of Assessing Officers. (2013, April). Standard on ratio studies. Retrieved from https://www.iaao.org/wp-content/uploads/Standard_on_Ratio_Studies.pdf (Accessed: 2025-02-17)
Kolbe, J., Schulz, R., Wersing, M., & Werwatz, A. (2012). Location, location, location: Extracting location value from house prices (Vol. 2012). SFB 649, Economic Risk.
Kolbe, J., Schulz, R., Wersing, M., & Werwatz, A. (2019). Land value appraisal using statistical methods. Zeitschrift für Immobilienökonomie, 5, 131–154.
Li, Q., & Racine, J. (2004). Cross-Validated Local Linear Nonparametric Regression. Statistica Sinica, 14(2), 485–512. Retrieved 2025-02-17, from https://www.jstor.org/stable/24307205 (Publisher: Institute of Statistical Science, Academia Sinica)
lincoln superuser. (2023, March). President's Message: Shall I Compare Thee to a Land Value Increment Tax? Retrieved 2025-02-17, from https://www.lincolninst.edu/publications/articles/2023-03-presidents-message-defining-land-policy-chatgpt-shakespeare/
McMillen, D., & Zabel, J. (2022, December). Special issue on land valuation: Introduction. Journal of Housing Economics, 58, 101881. Retrieved 2025-02-17, from https://linkinghub.elsevier.com/retrieve/pii/S1051137722000535 doi: 10.1016/j.jhe.2022.101881
Mills, E. S. (1998). The economic consequences of a land tax. In D. Netzer (Ed.), Land value taxation: Can it and will it work today? (pp. 31–48). Lincoln Institute of Land Policy.
Nadaraya, E. A. (1964). On Estimating Regression. Theory of Probability and its Applications, 9(1), 2. Retrieved 2025-02-17, from https://www.proquest.com/docview/913507046/abstract/31C6A84FC89240BBPQ/1 (Num Pages: 2 Place: Philadelphia, United States Publisher: Society for Industrial and Applied Mathematics) doi: 10.1137/1109020
Philadelphia Office of Property Assessment. (2022, May). Tax year 2023 mass

appraisal valuation methodology. Retrieved from https://www.phila.gov/media/20220525080608/tax-year-2023-mass-appraisal-valuation-methodology.pdf (Accessed: 2025-02-17)

Seabold, S., & Perktold, J. (2010). statsmodels: Econometric and statistical modeling with python. In 9th python in science conference.

Sieg, H. (2020). Urban Economics and Fiscal Policy. Princeton University Press. (Google-Books-ID: LL_kDwAAQBAJ)

Walczak, J. (2024, November). Confronting the new property tax revolt. Tax Foundation. Retrieved from https://taxfoundation.org/research/all/state/property-tax-relief-reform-options/

Wang, L., Brown, L. D., & Cai, T. T. (2011, January). A difference based approach to the semiparametric partial linear model. Electronic Journal of Statistics, 5(none), 619–641. Retrieved 2025-02-17, from https://projecteuclid.org/journals/electronic-journal-of-statistics/volume-5/issue-none/A-difference-based-approach-to-the-semiparametric-partial-linear-model/10.1214/11-EJS621.full (Publisher: Institute of Mathematical Statistics and Bernoulli Society) doi: 10.1214/11-EJS621

Watson, G. S. (1964). Smooth Regression Analysis. Sankhyā: The Indian Journal of Statistics, Series A (1961-2002), 26(4), 359–372. Retrieved 2025-02-17, from https://www.jstor.org/stable/25049340 (Publisher: Springer)

Yatchew, A. (1997, December). An elementary estimator of the partial linear model. Economics Letters, 57(2), 135–143. Retrieved 2025-02-17, from https://linkinghub.elsevier.com/retrieve/pii/S0165176597002188 doi: 10.1016/S0165-1765(97)00218-8