Metropolitan Land Values[1]

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Abstract

We estimate the first cross-sectional index of transaction-based land values for every U.S. metropolitan area. The index accounts for geographic selection and incorporates novel shrinkage methods using a prior belief based on urban economic theory. Land values at the city center increase with city size, as do land-value gradients; both are highly variable across cities. Urban land values are estimated at more than two times GDP in 2006. These estimates are higher and less volatile than estimates from residual (total - structure) methods. Five urban agglomerations account for 48 percent of all urban land value in the United States.

JEL Codes: C43, R1, R3

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1 Introduction

We estimate the first index of land values across U.S. metropolitan areas that is based on directly-observed market transactions and cross-sectionally comparable. Standard economic theory, e.g. Roback (1982), Brueckner (1983), and Albouy (2016), suggests that this index captures differences in the combined value of household amenities, employment, and building opportunities, ignoring cross-metro externalities. Urban land values have been central to questions of wealth, income, and taxation since the seminal works of Ricardo (1821) and George (1884).

Unfortunately, market data on land values have been notoriously piecemeal and subject to numerous measurement challenges. Flow of Funds (FOF) accounts of the Federal Reserve stopped publishing series for land value in 1995 because of accuracy concerns made plain by negative values inferred for land. We aim to overcome these challenges using a large national data set of market transactions of land from the CoStar COMPS database and an econometric model informed by urban theory. Our estimates of urban land values prove to be higher and more stable than values implied by the FOF.

Our indices of both central and average land values have intuitive properties. While they vary considerably, the indices increase with city area, providing nuanced support for the monocentric city model of Alonso (1964), Mills (1967), and Muth (1969). The highest central land values are found in New York, Chicago, Washington, San Francisco, and Los Angeles. In these cities, central values are 21 times higher than peripheral values 10 miles away, although across all cities the (unweighted) average ratio of central to peripheral values is only 4. Over their entire urban areas, New York, Jersey City, Honolulu, San Francisco, and Los Angeles-Long Beach have the highest average values, which are 82 times higher than those in the lowest five cities. Values in 2009 averaged \$373,000 per acre, down from \$624,000 in 2006, as the total value of urban land fell from \$28 to \$18 trillion, or from 2.2 to 1.3 times GDP.

2 Description of Transactions Data and Urban Land Area

Our primary data source is the CoStar COMPS database, with land transaction prices recorded between 2005 and 2010.[1] CoStar provides fields containing the price, lot size, address, and a "proposed use" for each property. We exclude transactions CoStar has marked as non-arms length, without complete information, that feature a structure, are over 60 miles from the city center, or are less than \$100 per acre. The remaining dataset contains 68,756 observed land sales.[2]

The "cities" we examine correspond to 1999 OMB definitions of Metropolitan Statistical Areas (MSAs). Some MSAs, known as Consolidated MSAs (CMSAs) are divided into constituent "Primary" MSAs, which we treat as separate cities. In 2000, all MSAs accounted for 80 percent of the U.S. population. Because MSAs consist of counties, which often contain a large amount of agricultural land, we consider only land that is part of an urban area by 2000 Census definitions. The main requirement is that the area consists of contiguous block groups with a population density of

[1]The CoStar Group claims to have the commercial real estate industry's largest research organization. The COMPS database provided by CoStar University is not publicly available, but can be accessed for free by academics. The data include transaction details for all types of commercial real estate. We use every sale CoStar considers "land." Recently, a small literature has used this data for analyses within metro areas. Haughwout et al. (2008) demonstrate the data's extensive coverage and construct a land price index for 1999 to 2006 within the New York metro area. Kok et al. (2014) document land sales within the San Francisco Bay Area, and relate sales prices to topographical, demographic, and regulatory features. Nichols et al. (2013) construct a panel of land-value indices for 23 metros from the 1990s to 2009. These indices are for use over time and are not comparable across metros.

[2]The appendix provides information on the treatment of the data as well as some descriptive statistics.

over 1,000 residents per square mile (1.56 per acre), with a total population of over 2,500.

We take city centers to be the City Hall or Mayor's office of each city. Many MSA names contain multiple cities, e.g., Minneapolis-St. Paul. We address this by considering each named city as having its own center. Land parcels within the MSA are assigned to the city center closest in Euclidean distance. In such cases, our central values average the named centers.

Appendix Figure A.1 displays the geographic pattern of land sales for four CMSAs: New York, Los Angeles, Chicago, and Houston. The figure shows that land sales are well-dispersed throughout the metro areas, with sales activity more frequent near city centers.[3]

3 Econometric Methods

There are two major obstacles to constructing a cross-metropolitan land value index from observed transactions data. First, observed transactions are not a random sample of all parcels in a city. Second, we observe few sales in many smaller metro areas, reducing the reliability of the estimates. Our econometric methods try to overcome both of these obstacles.

[3]Land transactions are not randomly distributed over space. Yet, as Haughwout et al. (2008) comment on the New York data, "Overall, vacant land transactions occurred throughout the region, with a heavy concentration in the most densely developed areas ...". As Nichols et al. (2013) discuss, it is impossible to correct for all types of selection bias without observing transaction prices for unsold lots, a logical contradiction. Fortunately, the literature has generally found selection bias to be minor for land and commercial real estate prices. Colwell and Munneke (1997), studying land prices in Cook County, IL, report, "The estimates with the selection variable and those without are surprisingly consistent for each land use." Studying the office market in Phoenix, Munneke and Barrett (2000) find, "the price indices generated after correcting for sample-selection bias do not appear significantly different from those that do not consider selectivity bias." In their construction of metro price indices, Munneke and Barrett (2001) report, "Little selection bias is found in the estimates." Finally, Fisher et al. (2007), in their study of commercial real estate properties, state "sample selection bias does not appear to be an issue with our annual model specification." Nevertheless, we correct for selection bias on observables below in section 3.

3.1 Regression Model of Land Values over Space and Time

Following the monocentric city model, we take each city j as having a fixed center, with coordinates $\mathbf{z}_j^c$. Land values, r, vary according to a city-specific polynomial in the distance metric, $D(\mathbf{z}_{ij}, \mathbf{z}_j^c)$, between plot i's coordinates $\mathbf{z}_{ij}$ and the center. City-center values α_{jt} may vary by year, t; coefficients δ_{jk}, which determine the shape of the value-distance gradient, are held constant over time due to limited sample sizes:

$$\ln r_{ijt} = \sum_{t=2005}^{2010} \alpha_{jt} + \sum_{k=1}^{K} \delta_{jk} \left[D(\mathbf{z}_{ij}, \mathbf{z}_j^c)\right]^k + X_{ijt}\beta + e_{ijt}, \quad e_{ijt} \sim \text{ i.i.d. } N(0, \sigma_e^2). \tag{1}$$

Controls X_{ijt} include proposed use and lot size. The idiosyncratic error term, e_{ijt}, follows an independent and identically distributed normal distribution.[4]

Figure 1a shows estimated first-order and fourth-order polynomials for the Houston MSA, along with the underlying transaction prices. Both polynomials slope downward with distance, but the fourth-order polynomial reveals a subtler distance function.

3.2 Shrinkage Estimation and Its Target

To deal with limited sample sizes we develop a hierarchical model. It "shrinks" metro-level estimates towards a national average function. This function target depends on each city's urban area,

[4]We define $D(\mathbf{z}_{ij}, \mathbf{z}_j^c) = \ln\left(1 + ||\mathbf{z}_{ij} - \mathbf{z}_j^c||\right)$, using Euclidean distances in miles. Adding one in the logarithm argument creates two desirable features. First, it dampens the effect of small changes in distance very close to the city center. Second, it makes D operate as a distance metric, so that the α_{jt} coefficients may be interpreted as (finite) log land values at the city center. Since the true gradient may vary along rays with different angles from the center, this serves largely as an averaging technique, used for comparisons across cities. Some cities have land rent gradients that decline monotonically from the center all the way to their agricultural fringe. Others see a dip in central-city values that rise again for the inner suburbs, before declining again at the fringe.

A_j. We begin by decomposing the central value α_{jt} into two components, $\alpha_{jt} = \alpha_j + \alpha^\star_{jt}$, where $\alpha^\star_{j2005}$ is normalized to zero. The time-varying component follows the prior $\alpha^\star_{jt} \sim N(\tau_t, \sigma_t^2)$. Vectorizing the distance coefficients $\boldsymbol{\delta_j} = [\delta_{j1}\ \delta_{j2}\ \cdots\ \delta_{jK}]'$, (time-invariant) cross-sectional priors are modeled

$$\begin{bmatrix} \alpha_j \\ \boldsymbol{\delta_j} \end{bmatrix} = \begin{bmatrix} a_0 & a_1 \\ \mathbf{d_0} & \mathbf{d_1} \end{bmatrix} \begin{bmatrix} 1 \\ \ln A_j \end{bmatrix} + \begin{bmatrix} e_{\alpha,j} \\ \mathbf{e_{\delta,j}} \end{bmatrix}, \quad \begin{bmatrix} e_{\alpha,j} \\ \mathbf{e_{\delta,j}} \end{bmatrix} \sim \text{ i.i.d. } N\left(\begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix}, \begin{bmatrix} \Sigma_{\alpha\alpha} & \boldsymbol{\Sigma_{\alpha\delta}} \\ \boldsymbol{\Sigma_{\delta\alpha}} & \boldsymbol{\Sigma_{\delta\delta}} \end{bmatrix} \right). \tag{2}$$

This technique essentially constructs a "metacity" described by the parameters $a_0, a_1, \boldsymbol{\delta_0}$, and $\boldsymbol{\delta_0}$. The metacity provides the land rent gradient typical of a city with area A_j. This area adjustment is important as larger cities typically have higher central land values. These land values descend and dovetail with agricultural (or other non-urban) values at different rates from the center than in smaller cities. The model allows for a full covariance matrix between the random components of the intercept and distance coefficients, $e_{\alpha,j}$ and $\mathbf{e_{\delta,j}}$.

When all other parameters are known and $\alpha^\star_{jt} = 0$, the best linear unbiased predictor (BLUP) for $[\alpha_j, \boldsymbol{\delta_j'}]'$ is a weighted average between their prior mean and conventional metro-level (fixed effect) estimates, $[\widehat{\alpha}_j, \widehat{\boldsymbol{\delta}}_{\boldsymbol{j}}]'$:

$$\begin{bmatrix} \widetilde{\alpha}_j \\ \widetilde{\boldsymbol{\delta}}_{\boldsymbol{j}} \end{bmatrix} = \mathbf{W_j} \begin{bmatrix} a_0 & a_1 \\ \mathbf{d_0} & \mathbf{d_1} \end{bmatrix} \begin{bmatrix} 1 \\ \ln A_j \end{bmatrix} + (\mathbf{I} - \mathbf{W_j}) \begin{bmatrix} \widehat{\alpha}_j \\ \widehat{\boldsymbol{\delta}}_{\boldsymbol{j}} \end{bmatrix} \tag{3}$$

where the weighting matrix $\mathbf{W_j}$ accounts for the amount of shrinkage in city j. This shrinkage term falls with the number of observations in city j and rises with the uncertainty in the prior

$(\mathbf{\Sigma}_{\alpha\alpha}, \mathbf{\Sigma}_{\delta\alpha}, \mathbf{\Sigma}_{\delta\delta})$ and the idiosyncratic error term (σ_e^2).

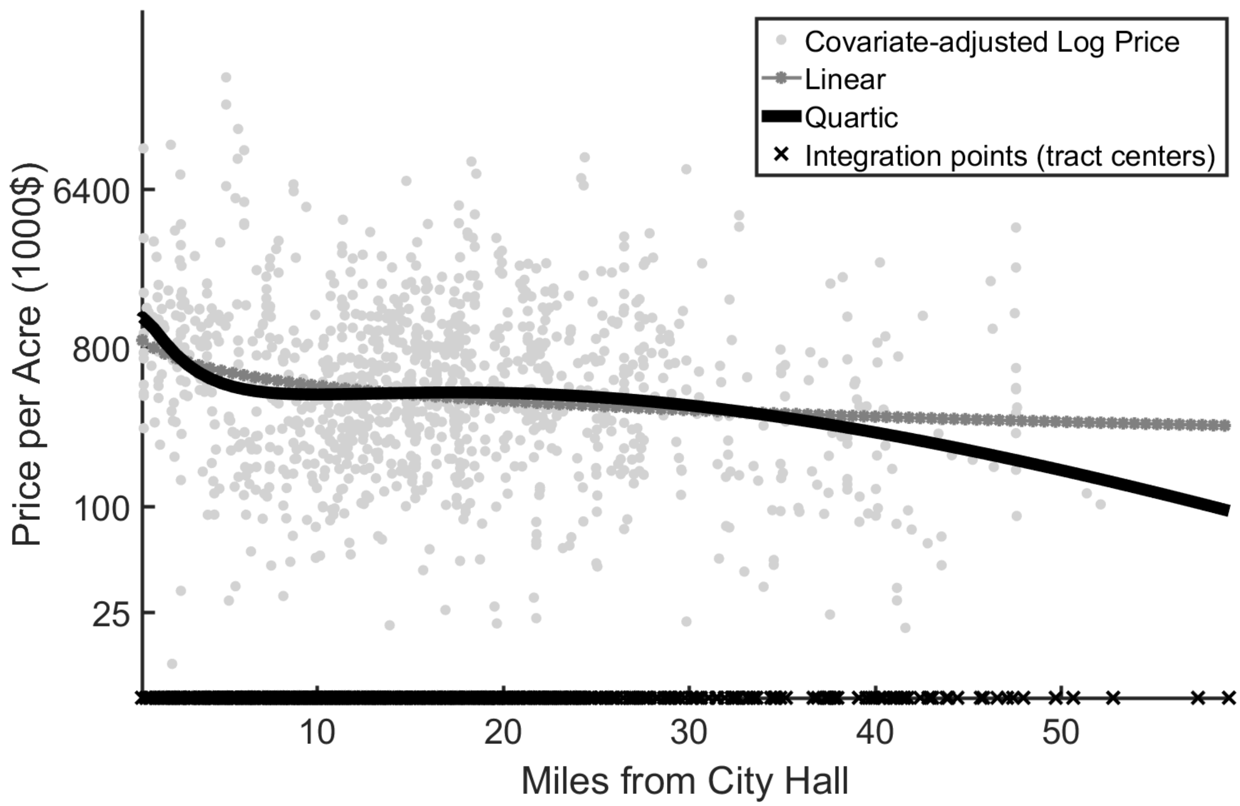
The second component in the intercept, α^*_{jt}, captures the city-specific time trend. By similar logic, we shrink the MSA-level time trend toward the national level time trend, τ_t, where the degree of the heterogeneity in MSA-level time trends is allowed to change over time through σ_t^2.

Our empirical model is then completed by specifying the joint distribution of error terms, controls, and the prior. We assume that observed control variables are random and strictly exogenous. That is, for each city j, the error-term vector $e_j = \{\{e_{ijt}\}_{i=1}^{n_j}\}_{t=2005}^{2010}$ is uncorrelated with the control vector $\{\{D(\boldsymbol{z_{ij}}, \boldsymbol{z_j^c}), ..., D(\boldsymbol{z_{ij}}, \boldsymbol{z_j^c})^K, \{X\prime_{ijt}\}_{t=2005}^{2010}\}_{i=1}^{n_j}, \ln A_j\}$ and the random component of the coefficient vector $\{e_{\alpha,j}, \boldsymbol{e'_{\delta,j}}, \alpha^\star_{j2006}, ..., \alpha^\star_{j2010}\}$. In addition, the random component of the coefficient vector is uncorrelated with the control vector *a priori*.

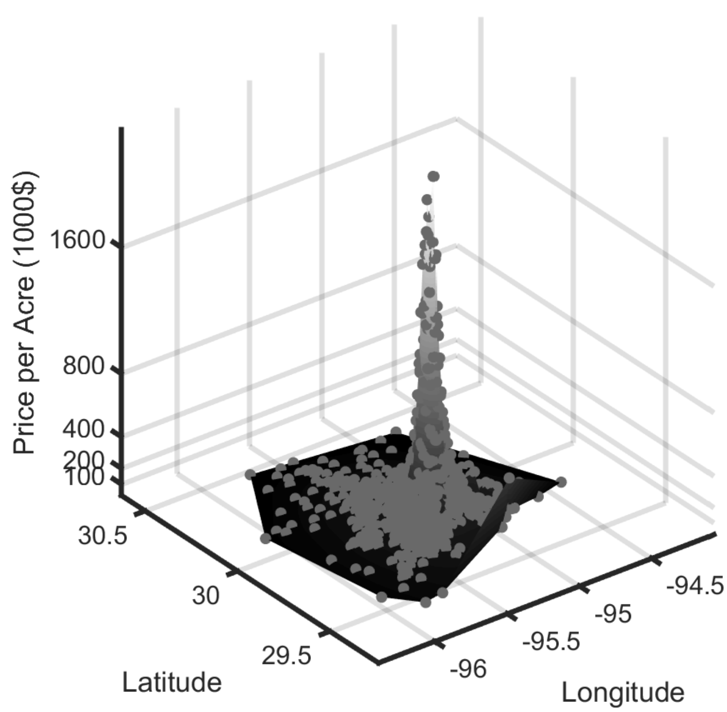
In practice, to estimate the BLUP for the random intercept and gradient parameters, the unknown fixed parameters $(\beta, a_0, a_1, \mathbf{d}_0, \mathbf{d}_1)$ and variance parameters $(\sigma^2, \Sigma_{\alpha\alpha}, \mathbf{\Sigma}_{\boldsymbol{\alpha\delta}}, \mathbf{\Sigma}_{\boldsymbol{\delta\delta}})$ must also be estimated. To do this, we adopt an empirical Bayes-type approach in which these parameters are found by maximizing the marginal likelihood with a flat improper prior. Then, we obtain estimates for $[\alpha_{jt}, \boldsymbol{\delta'_j}]'$ by substituting these estimates into the posterior mean formula as if the fixed and variance parameters were known. Appendix B describes the shrinkage procedure in much greater detail.

Figure 1: Example of Land Value Gradient Estimates for the Houston, TX Metro Area

(a) Estimated Distance Polynomial with $D = \ln(1 + \text{mileage})$



(b) Estimated Land Value Surface with Census Tract Centroids



3.3 Integrating Land Values Over the Urban Area

We use the estimated land value functions to compute average land values over each city's urban area in each year. For each census tract l in city j in year t, we calculate the predicted land value $\hat{r}_{ljt}$ at the tract centroid. The predicted value is based on the expected characteristics X (planned use and lot size) of the tract, conditional on the city, distance from the center and coast, and observed transaction data. We then assign that average value to the entire tract.[5] This value is then multiplied by the area of each tract A_{jl}, excluding any non-urban block groups. The total value of land in city j is then $R_{jt} = \sum_l A_{jl}\hat{r}_{ljt}$, and the average value is $r_{jt} = R_{jt}/A_j$. In other words, total land values in city j are the volume of the estimated land value "cone," while the average land value is the cone's average height. Figure 1b displays the estimated cone for the Houston MSA, with the small dots representing Census tract centers. Very high land values at the city center are clearly visible in the figure, which also shows slightly elevated values for the Census tracts near the coast.

The estimated "meta-city" allows us to impute land values for metros with no observations, in which case $\boldsymbol{W_j} = \boldsymbol{I}$. Tract values are imputed based on typical intercepts and gradients for cities of size A_j in year t, based on their position relative to the closest city center and coastlines.

3.4 Model Selection and Cross-Validation

The cross-validation exercise summarized in table 1 assesses the performance of several econometric specifications, as detailed in appendix B. The exercise fixes a number of MSAs, and retains

[5] We include only tract centers within 60 miles of the city center. To obtain the predicted characteristics X we build and estimate a model for characteristics X that is a similar but simplifed version of the hierarchical model used for the land price. The procedure and required assumptions for the land value prediction at the tract centroid is discussed at length in section B.3.

Table 1: Econometric Model Cross-Validation Results

	Model Specification						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: 3 observations per city-year							
Mean Squared Error	1.640	1.143	0.939	0.938	0.936	0.936	0.935
Bias	-0.004	0.013	0.016	0.013	0.013	0.013	0.013
Variance	1.586	1.105	0.910	0.909	0.907	0.906	0.905
Panel B: 30 observations per city-year							
Mean Squared Error	1.449	0.912	0.904	0.902	0.898	0.897	0.896
Bias	-0.004	-0.003	0.001	0.000	0.001	0.001	0.000
Variance	1.441	0.907	0.899	0.898	0.893	0.892	0.891
Shrunken?	No	No	Yes	Yes	Yes	Yes	Yes
Polynomial Order - Distance	0	1	1	2	3	4	4
Polynomial Order - Lot Size	0	1	1	1	1	1	3

Out-of-sample cross-validation exercise described in detail in the appendix. Column 1 shows results of a naive model that is the simple average of values per acre. Columns 2 through 7 contain controls for all covariates in Appendix Table A.1. Panel A shows results for exercise in which 3 observations per city-year are combined with all out-of-city data to predict remaining land values in city. Panel B shows results for exercise in which 30 observations per city-year are combined with all out-of-city data to predict remaining land values in city. Out of sample predictions in both panels were conducted in 58 cities that had at least 50 observations per year for at least two years.

a few observations per year. It then uses those few observations and the model estimates from other MSAs to predict the values of the non-retained observations. The mean squared error (MSE) between the predicted price and the actual price of these non-retained observations is used to assess the model. Results in Panel A retain 3 observations per city-year; panel B retains 30.

The first specification, in column 1, is of a "naive" model that takes the (geometric) average value per acre of all sales by metro. It establishes a baseline for other models to improve upon. The second column shows the results from a simple version of model (1), with only linear city-specific terms in distance ($K = 1$), as well as city-time specific intercepts, measures of coastal proximity, controls for proposed use, and a linear term in log lot size. This basic econometric model lowers the mean squared error (MSE) over the naive model substantially by reducing the variance of the estimates. The third specification applies the empirical Bayes shrinkage technique according to the prior (2), allowing both intercepts and gradients to be random. As expected, this produces a substantial improvement by further reducing the variance. Thus, both the monocentric regression model and shrinkage help overcome the obstacles of small samples and non-random locations, as seen by lower prediction errors.

The rest of the table considers what are minor improvements. The fourth through sixth columns contain add additional distance polynomials to the model in 3. Allowing for a more flexible distance gradient reduces the MSE only moderately. The final column includes a cubic polynomial in log lot size, which also slightly improves the prediction. As further terms produce no noticeable improvement, we take the model with Bayesian shrinkage, a quartic polynomial in distance, and a cubic polynomial in log lot size as our preferred specification.

4 Cross-Sectional Results

4.1 Patterns in the Data

Figures 2a-2c plot estimated central land values, the ratio of those values to values 10 miles from downtown, and average land values, each against the urban area of the metro area.[6] The grey dots represent the unshrunken estimates; the dark dots, the shrunken estimates: the vertical distances between the two display how much the Bayesian approach shrinks the estimates. Larger cities,

[6] We take land values one-half mile from the point defined at the center as our measure of central land values.

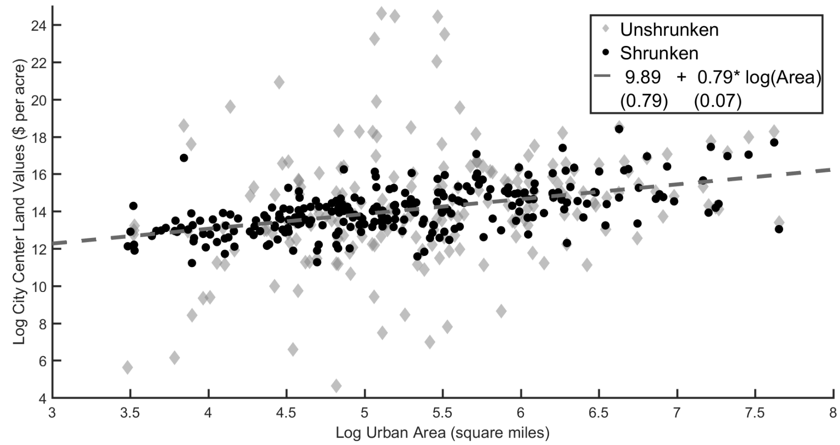
which feature more observations, experience less shrinkage, as the additional observations make the prior less important.

The dashed upward-sloping line of best fit in Figure 2a reflects the tendency of larger cities to have more expensive central land. A ten-percent increase in a city's footprint implies an 8-percent increase in the central land value. The upward-sloping fitted line in Figure 2b reveals that land values in larger cities are much higher centrally than values 10 miles away. For the smallest cities the gradient is typically nearly flat. In large cities, the ratio is much larger, but highly variable, even after shrinkage. Together, these two patterns lead to the weaker, but still positive, correlation between city size and average urban land values in Figure 2c. These empirical results are generally supportive of a monocentric city with convex rent gradients. Theoretically, these gradients steepen towards the center as firms and households sort according to how their bid per acre varies with distance. Furthermore, agents substitute away from using land as it rises in price.[7]

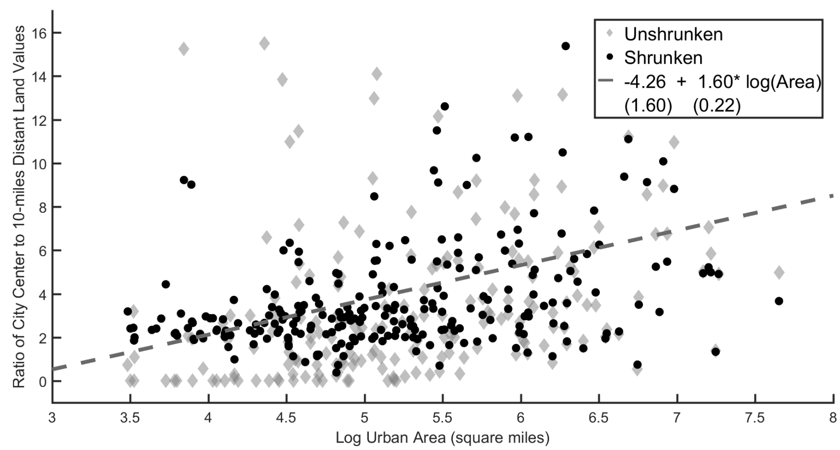
[7]Combes et al. (2016) also find that land-rent gradients are steeper in large French cities than in small ones.

Figure 2: Estimation Results - All Metro Areas

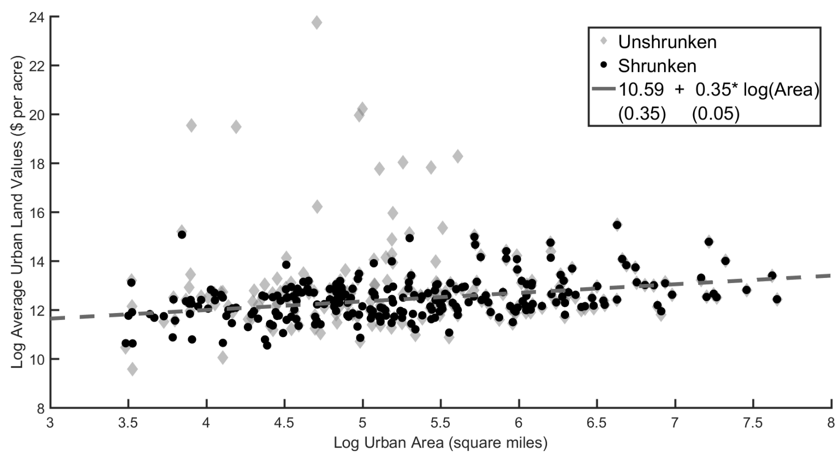
(a) Central Land Values



(b) Ratio of Central to 10-mile Distant Land Values



(c) Average Land Values



While our main interest is estimating land values and their cross-sectional differences by MSA, it is worth briefly describing the estimated coefficients on the model covariates, presented in appendix Table A.1. The most important predictor of log value per acre is log lot size, which enters the regression model as a cubic polynomial. The estimates imply that price per acre is declining in lot size over the size range. This is a standard result called the "plattage effect", described by Colwell and Sirmans (1993) in this *Review* as "a well-known empirical regularity." It is often ascribed to costs of subdividing land parcels, arising both from infrastructure requirements and from zoning.[8]

Most of the planned use regressors have statistically and economically significant associations with land values. Retail, apartment, mixed use, and medical proposed uses have substantially higher values, while commercial, industrial, and multifamily uses have lower values. Lots with no planned use, or a planned use of "hold for development" or "hold for investment" also have lower values. Not surprisingly, within-metro land values rise with coastal proximity.

[8]With such costs, large lots may contain more land than is optimal for their intended use. For instance, a lot may have more land than is need to build an apartment building, but cannot be subdivided into two lots on which to build two apartment buildings. In that case, the price per acre of the large lot will be lower than if it contained the optimal amount of land for its intended use.

We have also computed our land value index using total parcel prices on the left-hand side variable in order to circumvent possible problems with division bias. If lot size is measured with error, then the coefficient estimates are subject to biases. In our log price per acre specification, classical measurement error in log size bias the first coefficient toward minus one. To check on the robustness of our fit, we re-compute the land value index based on the log of total prices instead. The fitted land values are virtually identical , and the correlation between the two land indices is essentially one. Essentially all that changes is the nature of the shrinkage estimation.

4.2 A Cross-Metropolitan Land Value Index

Table 2 presents urban land value estimates for selected metro areas.[9] The first two columns show the name of each MSA, and its rank out of 324 according to the estimated land value in our preferred model specification in column 7 of Table 1. Next are the urban (not total) areas of each metro, and the number of observed land sales. The fifth column presents average values from the naive model. Column 6 reports estimated central land values[10] using the preferred model, and column 7 presents estimated average values across the urban area. Column 8 reports the estimated ratio of central values to those 10 miles away. The last column provides the total value of urban land by metro, which is totalled at the bottom of the table.

The numbers in columns 5 and 7 contrast the role of the model-based estimator over the naive one. While the two are positively correlated with a coefficient of 0.86, the standard deviation of the naive estimates is 3.2 times higher than that of the model-based estimates. For instance, New York has the highest naively estimated value per acre, $26 million. Pittsfield, MA has the lowest naively estimated values, $17 thousand. In general, MSAs with high naively estimated values benefit from favorable covariates, such as small lot sizes.

Overall, our estimates cover 76,581 square miles of urban land. The total estimated value of this land is $25,025 billion on average over the sample period. The average value of urban land was $511,000 per acre, with an unweighted standard deviation of $519K across metro areas. This average implies a cost of roughly $100 K for a typical fifth-acre residential lot, or $2,000 for a typical parking spot.

[9] Estimates for all MSAs in the sample are available in Table A.2 of the appendix.

[10] We take estimated values one-half miles from downtown as our estimate of city center land values.

Table 2: Selected Metropolitan Land Value Indices, 2005-2010

Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	*Land Values - $000s/Acre* Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Urban Land Value ($ billions)
1	New York, NY	749	1,603	26,139	123,335	5,264	22.3	2,524.4
2	Jersey City, NJ	47	43	7,667	9,554	3,305	8.8	98.8
3	Honolulu, HI	198	56	4,357	16,256	3,290	7.0	416.3
4	San Francisco, CA	300	152	8,722	25,446	3,239	9.3	622.8
5	Los Angeles-Long Beach, CA	1,359	1,760	3,709	16,801	2,675	5.5	2,326.8
6	Orange County, CA	494	233	3,163	3,208	2,595	1.3	820.5
7	San Jose, CA	305	217	2,580	3,552	2,347	1.6	458.3
8	Miami, FL	372	1,233	3,052	4,478	1,794	3.2	427.5
9	Stamford-Norwalk, CT	179	19	2,753	2,740	1,505	3.2	172.4
10	Bergen-Passaic, NJ	316	79	1,957	4,145	1,423	3.7	287.7
16	Washington, DC-MD-VA-WV	1,458	1,840	3,548	36,913	1,214	32.6	1,133.0
22	Las Vegas, NV-AZ	317	2,553	1,193	1,841	849	2.4	172.4
26	Chicago, IL	2,035	3,511	1,455	37,632	663	35.1	863.3
27	Boston, MA-NH	1,295	122	1,243	8,457	600	9.8	497.5
32	Denver, CO	536	2,015	828	7,586	539	18.6	185.1
52	Phoenix-Mesa, AZ	897	5,946	370	3,529	452	8.4	259.4
99	Dallas, TX	1,057	811	454	2,774	305	10.1	206.4
118	Houston, TX	1,341	1,143	423	2,813	272	9.4	233.1
120	Detroit, MI	1,426	679	456	2,321	270	6.6	246.6
130	Atlanta, GA	2,105	5,229	402	1,750	251	5.5	338.6
227	Pittsburgh, PA	1,003	240	433	1,772	156	10.6	100.0
322	Glens Falls, NY	33	21	46	65	45	2.6	0.9
323	Jackson, MI	57	8	49	74	38	3.0	1.4
324	Jamestown, NY	46	10	43	63	30	2.1	0.9
	Total U.S.	76,581	68,756	-	-	-	-	25,024.8
	Simple Average U.S.	235	212	591	1,672	344	3.7	76.8
	Simple Std. Dev. across Metros	304	592	1,660	7,472	519	3.6	226.6
	Weighted Average U.S.	-	739	1,052	5,068	511	6.5	244
	Wtd. Std. Dev. across Metros	-	1,214	2,701	13,850	715	7.2	430.9

MSAs are ranked by average urban land values. Land-value data from CoStar COMPS database for years 2005 to 2010. Naive model is simple average of observed prices per acre. Estimated allows land values to depend on quartic polynomial in log distance from city center plus one mile, with random coefficients. City center land values are for one-half mile from downtown, and mile 10 land values are for 10 miles from downtown. Weighted statistics for U.S. are weighted by total metropolitan urban area. Standard deviations are unweighted. See appendix table A.2 for complete list of MSAs. Averages and standard deviations for the U.S. do not include MSAs for which there were no observed land sales.

The highest central land values are found in New York, at a whopping \$123 million per acre. The remaining top 5 are Chicago, Washington D.C., San Francisco, and Los Angeles-Long Beach, with values between \$17M and \$38M. With the exception of tightly-regulated Washington, all of these central areas are known for their towering skylines.

The New York PMSA has the highest average values as well, \$5.3 million per acre, even after averaging in several counties in addition to New York County (Manhattan). The next three highest averages are found in quality locations with smaller land areas. For instance, Jersey City, a valuable strip of 47 square miles with great views of Manhattan, is second with an average value of \$3.3M per acre. Honolulu takes third place, also at \$3.3M per acre, and is loaded with a scenic views, miles of coastline, and a desirable climate. San Francisco, which completes the almost three-way tie for second, is famous for similar natural amenities, as well as a booming business environment. In fifth place, Los Angeles-Long Beach has average values of \$2.7M per acre over its extended area of 1,359 square miles, which is unsurprising for the second most populous metro area.

The top ten cities in terms of average values are all on or near salt water coasts. Average land values are more moderate in the Midwest and South: Chicago has an average value of \$663 thousand per acre, while Pittsburgh has an average of \$156K. Dallas, Houston, and Atlanta have averages values roughly in the \$250K-\$300K per acre range. The lowest values are found in small cities such as Glens Falls, NY, Jackson, MI, and Jamestown, NY, at less than \$50K per acre.

Although the estimated rank correlation between central and average land values is 0.85, the ratio of central values to those 10 miles away varies considerably. The weighted (unweighted) average is 3.7 (6.5), with a standard deviation of 3.6 (7.2). Chicago, with its circumscribed Loop District, has the highest ratio, 35.1, followed by Washington D.C., at 32.6. The tenth percentile ratio of central to 10-miles distant values is 1.6. San Jose, CA and Orange County, CA are the most valuable and prominent cities beneath that threshold, reflecting their decentralized urban structures.

The New York PMSA has the greatest total land value of any metro, at roughly $2.5 trillion.[11] The Los Angeles-Long Beach PMSA is not far behind, with a total value of $2.3T. When cities are aggregated to the CMSA level, the top five for total urban land values are New York, Los Angeles, San Francisco, Washington, and Chicago, which together account for 48 percent of the value of all urban land in the United States.

4.3 Comparing Transaction- and Residual-based Estimates

A common approach to measure land values is to treat them as the residual difference between a property's entire value and the estimated value of its structure.[12] A caveat of this method is that it equates the market value of a structure with its replacement value, neglecting adjustment costs in building and irreversibilities in investment (Glaeser and Gyourko, 2005). When the market value of structures falls below replacement costs, the residual method assigns the entire decrease to land values. The residual method can even infer negative value to land, as Davis and Heathcote (2007) do for residential land in 1940; Larson et al. (2015) show that the Flow of Funds approach implied the value of land in the corporate business sector in 2009 was worth *negative* $178 billion (Bureau of Economic Analysis, 2013). It seems highly unlikely that there were no "buyers" in 2009 willing to be paid less than $178 billion to receive all the corporate land in the U.S.

Davis and Palumbo (2008), or "DP," use the residual method to estimate an index of land values across 46 metros. Despite the differences in measurement and intended coverage, we attempt to

[11]Barr et al. (2016) estimates a geometric average value of $991 billion for the island of Manhattan alone (less than 23 square miles) during that time. Therefore, we consider our estimates of New York land values, while high in absolute terms, to be within reason.

[12]Case (2007) explains how to use FOF data to impute land values in this way, using the replacement cost of housing structures.

compare our index to their theirs.[13] To compare acres and lots, we estimate average residential lot acreage by metro, and divide the DP numbers by this acreage. To aggregate the DP values, we multiply their estimated value per lot by the number of housing units in urbanized Census block groups in the year 2000, counting rental units as having half the land as an owned unit, which roughly reflects national averages. This aggregation method avoids estimating acreages, but misses non-residential land.[14] Appendix Table A.3 contains the estimates for the 45 MSAs in both samples, which are plotted in Figure 3.

Our transactions-based estimates imply higher land values than the residual-based estimates, \$722K vs. \$392K per acre. Across metros, the correlation coefficient between the two is 0.72. The aggregated DP and transaction numbers are more strongly correlated, with a coefficient of 0.95. Figure 3a contrasts the average values per acre, while Figure 3b contrasts the aggregate land values for each city: recall these are for all urban land in our transaction index, and for residential land only in the DP index. Our transaction index is higher than the DP index for nearly every city.

Looking at individual cities, both indices imply average land values over \$3M per acre for San Francisco, and values near \$60K for Charlotte. But for New York our transaction index implies urban land values of \$5.3M per acre vs. \$835K for the DP estimates. For Oklahoma City, our index is \$161K per acre, while the DP index implies \$24K per acre. These differences may arise from

[13]Their index is purely residential, for owner-occupiers only, and is estimated by lot. Our transaction index is for all urban land (including commercial and industrial), is for owners and renters, and is estimated by acre.

[14]We divide by average lot size, since DP report an arithmetic average of land value. This may introduce significant measurement error in some numbers. Using medians or geometric averages produces substantially higher average values per acre. The Davis and Palumbo (2008) index is quarterly; we take geometric averages to arrive at annual and whole-sample values. Matching our MSAs to their cities is typically straightforward using the name of the principal city. We do not match their estimates for Santa Ana to the Orange County, CA MSA, because we lack lot size information.

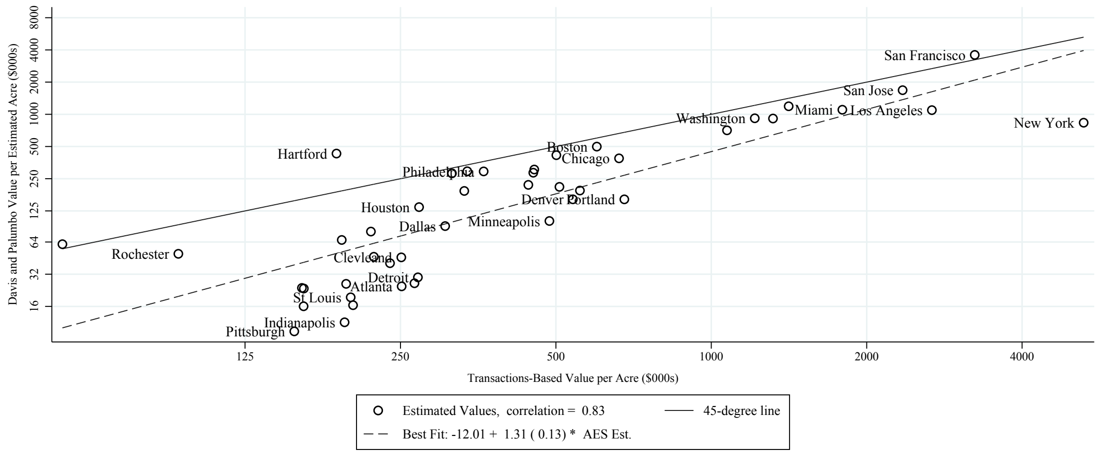
the differences in the types of land considered: our index includes very high value central land. Nevertheless, our data sources and estimation technique seem to play large roles. Furthermore, the value of transactional land should reflect available building opportunities, good or bad, while built-on land reflects the structure that is permitted de facto.[15]

Over time, our transaction index implies smaller price movements than the DP index within cities over the boom and bust cycle in our data. This is seen in figure 3c, which plots the estimated difference between the minimum and maximum annual estimated average land values within each city, expressed as a percentage of the maximum value. The average coefficient of variation of land values within the 45 cities according to our index was 0.24, versus 0.44 in the DP estimates. The greater volatility of the residual method is also seen in the time series for aggregate U.S. land values, which we consider below.

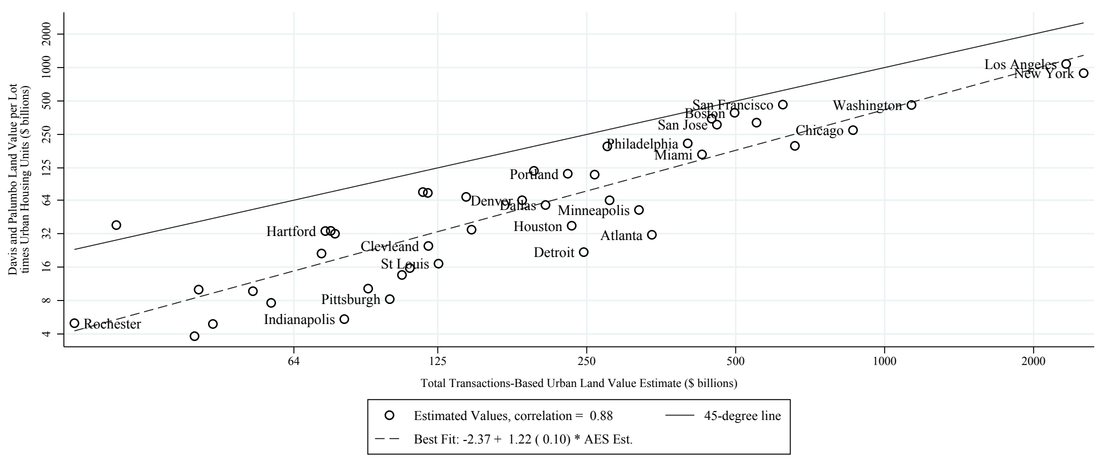
[15]As Davis and Heathcote (2007) note, the residual method attaches "the label 'land' to anything that makes a house worth more than the cost of putting up a new structure of similar size and quality on a vacant lot." Thus, the residual method will attribute higher costs stemming from inefficiencies in factor usage – e.g., geographic and regulatory constraints that hinder building – to higher land values. In a follow-up paper, Albouy and Ehrlich (2016) use differences in the value of housing prices from land and structure costs to measure the costs imposed by such constraints. See Glaeser and Gyourko (2017) for a related, but more reduced-form approach that assumes land is a fixed fraction of housing costs.

Figure 3: Comparison of Transactions-Based Index to Residual-Based Index

(a) Estimated Average Land Values per Acre



(b) Total Land Values



(c) Within-City Time Series Variation

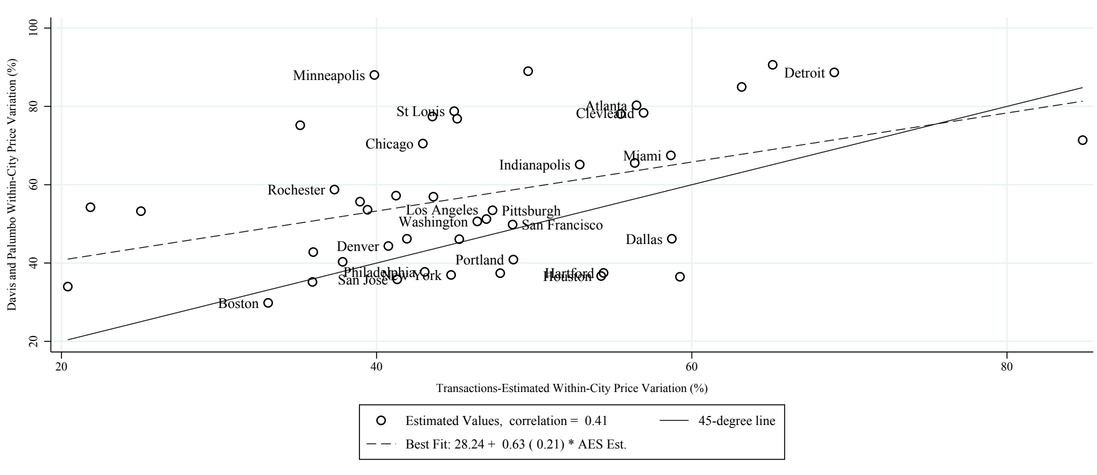


Table 3: Urban Land Values in the United States, 2005-2010

Year	Avg. Urban Land Value per Acre($)	Total Urban Land Value ($ billions)	Avg. Urban Land Value per Acre (Index, 2005 = 100)	Nominal GDP ($ billions)	Ratio of Total Urban Land Value to GDP	S&P CoreLogic Case-Shiller U.S. National HPI (Normalized to 2005=100)	Total Urban Land Value - Residual Method ($ billions)
2005	577,336	28,117	100.0	13,094	2.15	100.0	16,758
2006	623,950	30,387	108.1	13,856	2.19	106.8	16,931
2007	584,682	28,475	101.3	14,478	1.97	104.8	16,001
2008	513,413	25,004	88.9	14,719	1.70	95.5	9,569
2009	372,819	18,157	64.6	14,419	1.26	86.5	5,767
2010	392,683	19,124	68.0	14,964	1.28	84.2	6,234

Land-value data from CoStar COMPS database for years 2005 to 2010. Residual method calculates total real estate holdings at market value of nonfinancial businesses, households, and nonprofit organizations from Financial Accounts of the United States (formerly known as the Flow of Funds) and subtracts current-cost net stock of private structures from National Income and Product Accounts.

5 Aggregate Urban Land Values over Time

In this section, we sum our urban land values across metros to calculate annual aggregate urban land values for the United States.[16] Table 3 presents these totals.

Over our sample period, average values peaked in 2006 at $624K per acre, an increase of 8% from 2005. Average values then fell to near their 2005 levels in 2007, before declining precipitously. By 2009 the average value was roughly $373K per acre, 65% of its 2005 level. The ratio of aggregate urban land values to gross domestic product declined considerably as well. The ratio was 2.1–2.2 in 2005 and 2006 before declining to reach a value 1.28 by 2010.

For comparison, we construct a series for aggregate U.S. land values using the residual method

[16] Our sample includes observations from 324 out of the 331 MSAs and PMSAs in the 1999 OMB definitions. The combined imputed land value for the seven metros with no data is $61 billion, less than one-quarter a percent of our aggregate number.

based on FOF data (now the Financial Accounts of the U.S.). We sum the total value of real estate at market value held by non-financial non-corporate businesses, non-financial corporate businesses, and households and nonprofit organizations to arrive at the total market value of privately held real estate. We then subtract the current-cost net stock of private structures to arrive at a residual-based value for land. In 2006, the estimated value of real estate was $43.3 trillion, while structures were valued at $26.3T, implying that the total value of land was $16.9T. Our transactions-based estimate, in contrast, is $30.4T, nearly 80% higher, signifying that urban land is an even more important asset in the U.S. economy.

In addition to the methodological differences, the totals may differ because they cover different land. Our estimates are based on total metro urban areas, including public lands for roads, parks, and civic buildings. Assuming that the public owns urban land worth 40% of the total value, only $18.2T of land would be owned privately, which is much closer to the FOF numbers. On the other hand, the FOF numbers include land outside of metro-urban areas, which we exclude.

Land values calculated from the FOF fell even more dramatically than our series, down to only $5.8T in 2009, as opposed $14.4T. The peak-to-trough decline in the transactions-based index was 40%, substantially less than the 66% decline in the FOF.

Last, we consider how land values compare with housing prices. The final column of table 3 reports the S&P CoreLogic Case-Shiller U.S. National House Price Index, normalized to have value 100 in 2005. Overall, land values appear to have led house prices slightly, and were substantially more volatile than house prices over the sample period. This result is consistent with the Bostic et al. (2007) land leverage hypothesis that housing should have less volatile values than land.

6 Conclusion

Our analysis combines insights from the monocentric city model with empirical Bayesian methods to produce novel and plausible estimates of land values, even in metros with relatively thin data. These methods might easily be applied to estimate other city-wide measures, such as wages or property prices. Relative to residual approaches, our method suggests that urban land values may be higher, less volatile, and less likely to be negative. Furthermore, the model sheds light on the enormous differences in land values both across and within cities, with high central values providing indirect support for monocentric cities, albeit with heterogeneous value gradients.

We hope that the measures we provide may form the basis of reliable estimates of aggregate land wealth. With additional data, future modeling could be enriched to incorporate greater spatial structure and modifications for observed land uses. The cross-sectional index we provide should also prove useful to researchers examining differences in amenities and costs across metro areas.

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A Additional Data Notes

When a CMSA contains multiple PMSAs, we treat each PMSA as its own MSA for purposes of estimation and reporting. For instance, we treat the Washington, DC-MD-VA-WV and Baltimore, MD PMSAs as separate MSAs, although they are both parts of the Washington-Baltimore DC-MD-VA-WV CMSA. For New York City we use the Empire State Building as the city center rather than City Hall, following Haughwout et al. (2008). We treat each named city in an MSA with a hyphenated city name as having its own city center. For instance, we treat Minneapolis-St. Paul, MN-WI as containing two distinct cities, Minneapolis, MN, and St. Paul, MN. However, we treat such cities as belonging to one MSA for purposes of aggregating and reporting.

In the CoStar data, we consider 12 of the most common proposed uses, which are neither mutually exclusive nor collectively exhaustive. We consider an observation to feature a structure when the transaction record includes the fields for “ Bldg Type”, “ Year Built”, “ Age”, or the phrase “ Business Value Included” in the field “ Sale Conditions.” We geocoded the lot sales using the Stata “geocode” module of Ozimek et al. (2011). In addition to the exclusions discussed in the main text, we also exclude outlier observations with a listed price of less than $100 per acre or a lot size over 5,000 acres, or further than 60 miles away from the city center. We also exclude lots we could not geocode successfully.

Median lot size is 3.5 acres versus a mean of 26 acres. Land sales occur more frequently in the beginning of our sample period, with 21.7% of our sample from 2005 and 11.4% from 2010. Residential uses are common but by no means predominant in the sample: 17.6% of properties have a proposed use of single-family, multifamily, or apartments. 23.4% is being held for development or investment, and 16% of the sample had no listed proposed use.

B Computation

B.1 Estimation of Land Value Gradients: α_{jt} and δ_j

For notational convenience we rewrite the model in (1) as

$$\ln r_{ijt} = Z'_{ijt}\gamma_j + X_{ijt}\beta + e_{ijt}, \quad e_{ijt} \sim N(0, \sigma_e^2), \tag{A.1}$$

where $Z'_{ijt} = \left[1, D_{ij}, D_{ij}^2, D_{ij}^3, D_{ij}^4, 1_{ijt}^{2006}, 1_{ijt}^{2007}, 1_{ijt}^{2008}, 1_{ijt}^{2009}, 1_{ijt}^{2010}\right]$, with $D_{ij} = D(\mathbf{z}_{ij}, \mathbf{z}_j^c)$, and where 1_{ijt}^s is an indicator variable that takes value 1 if $s = t$ and 0 otherwise. The parameter vector γ_j collects city and time specific parameters with a multivariate normal prior distribution

$$\gamma_j = [\alpha_j, \delta_{j1}, \delta_{j2}, \delta_{j3}, \delta_{j4}, \alpha_{j,2006}, \alpha_{j,2007}, \alpha_{j,2008}, \alpha_{j,2009}, \alpha_{j,2010}]' \sim N(m_{\gamma,j}, V_{\gamma,0}) \tag{A.2}$$

where

$$m_{\gamma,j} = \begin{pmatrix} a_0 + a_1 A_j \\ \mathbf{b}_0 + \mathbf{b}_1 A_j \\ \tau \end{pmatrix} \quad \text{and} \quad V_{\gamma,0} = \begin{pmatrix} \Sigma_{\alpha\alpha} & \Sigma_{\alpha\delta} & \mathbf{0}_{(1\times 5)} \\ \Sigma_{\delta\alpha} & \Sigma_{\delta\delta} & \mathbf{0}_{(4\times 5)} \\ \mathbf{0}_{(5\times 1)} & \mathbf{0}_{(5\times 4)} & \Sigma_{\tau\tau} \end{pmatrix} \tag{A.3}$$

with $\tau = [\tau_{2006}, \tau_{2007}, \tau_{2008}, \tau_{2009}, \tau_{2010}]'$ and $\Sigma_{\tau\tau} = diag([\sigma^2_{2005}, \sigma^2_{2006}, \sigma^2_{2007}, \sigma^2_{2008}, \sigma^2_{2009}, \sigma^2_{2010}]')$. Conditional on fixed and variance parameters ($\theta = [\beta, a_0, a_1, \mathbf{b}_0, \mathbf{b}_1, \tau, \sigma_e^2, \Sigma_{\alpha\alpha}, \Sigma_{\delta\alpha}, \Sigma_{\tau\tau}]$) and observed data for city j, the posterior distribution of γ_j follows the multivariate normal distribution

$$\gamma_j|\theta, Data \sim N\left(\widetilde{m}_{\gamma,j}(\theta),\ \widetilde{V}_{\gamma,j}(\theta)\right) \tag{A.4}$$

with a posterior mean as the weighted average between the prior mean ($m_{\gamma,0}$) and the fixed effect estimate $\widehat{\gamma}_j = (Z_j'Z_j)^{-1}\left[Z_j'\left(\ln r_j - X_j\beta\right)\right]$:

$$\widetilde{m}_{\gamma,j}(\theta) = W_j(\theta)m_{\gamma,j} + \left[I - W_j(\theta)\right]\widehat{\gamma}_j(\theta) \quad \text{where } W_j(\theta) = \left[V_0^{-1} + \sigma_e^{-2}(Z_j'Z_j)\right]^{-1}V_0^{-1}. \tag{A.5}$$

Here we write Z_j, $\ln r_j$, and X_j as matrices that stack elements only relevant for the city j. The weighting matrix depends on the number of observations in the city j (n_j), the relative size of the prior variance (V_j), and the idiosyncratic error variance (σ_e^2). The posterior variance is

$$\widetilde{V}_{\gamma,j}(\theta) = \left[V_0^{-1} + \sigma_e^{-2}(Z_j'Z_j)\right]^{-1}. \tag{A.6}$$

It is well known that the posterior mean $\widetilde{m}_{\gamma,j}(\theta)$ is the best linear unbiased predictor for γ_j given θ and the observed data. In our application, we do not know θ. Instead of taking a full Bayesian approach and putting a prior on θ, we take the empirical Bayesian approach in which θ is calibrated by maximizing the following marginal likelihood (Laird and Louis, 1989):

$$\widehat{\theta} \in argmin_\theta\ L(data|\theta) = \int p(\ln r_{ijt}|Z, X, \theta, \gamma)d\gamma \tag{A.7}$$

where the γ is integrated out from the conditional posterior distribution an improper prior, $p(\gamma) \propto 1$, viz. Harville (1977). Then, we treat $\widehat{\theta}$ as a known and fixed quantity and use the following posterior distribution for the computation of land values and the prediction,

$$\gamma_j | Data \sim N\left(\widetilde{m}_{\gamma,j}(\widehat{\theta}),\ \widetilde{V}_{\gamma,j}(\widehat{\theta})\right). \tag{A.8}$$

One of the potential shortcomings of this approach is that it neglects uncertainty coming from the estimation of θ, and the resulting posterior distribution for γ_j underestimates uncertainty. Fortunately, we have a relatively large amount of data about θ (about 67,000 observations in total). Second, the practicality of our shrinkage estimator is evaluated by the out-of-sample forecasting evaluation. However, we note that a full Bayesian approach is possible (Zeger and Karim, 1991) at the cost of even longer computation time. We choose to take the empirical Bayes approach because of the out-of-sample evaluation of our shrinkage procedure.

B.2 Point Predictions for Land Values

Once we obtain the posterior distribution of γ_j, we can generate land value predictions. For the cross-validation exercise, we generate and evaluate point predictions for the log-price of the land parcels in the city j at time t with characteristic X^*_{ijt} and Z^*_{ijt} as the mean of the posterior predictive distribution. In the standard case when we observe at least some data in city j, the point prediction for the value of a land parcel is

$$\begin{aligned} \widehat{\ln r_{ijt}} &= \int \ln r_{ijt} p(\ln r_{ijt} | data, X^*_{ijt}, Z^*_{ijt}) d \ln r_{ijt} \\ &= \int\int \ln r_{ijt} p(\ln r_{ijt} | data, X^*_{ijt}, Z^*_{ijt}, \gamma_j) p(\gamma_j | data) d\gamma_j d \ln r_{ijt} \\ &= Z^{*'}_{ijt} \widetilde{m}_{\gamma,j}(\widehat{\theta}) + X^{*'}_{ijt} \widehat{\beta}. \end{aligned} \tag{A.9}$$

We can also generate predictions for the land in cities where we do not have observed transaction prices. This is based on our "metacity" for a city with area A_j, using the prior with estimated hyperparameters, $\widehat{\theta}$. . In this case, our prediction is just

$$\widehat{\ln r_{ijt}} = Z_{ijt}^{*'} m_{\gamma,j}(\widehat{\theta}) + X_{ijt}^{*'}\widehat{\beta}. \tag{A.10}$$

B.3 Computation of Land Values

For each census tract l in city j in year t, we calculate the predicted land value r_{ljt} at the tract centroid and assign that average value to the entire tract.

$$R_{jt} = \sum_{l=1}^{L} \widehat{r}_{ljt} A_l \tag{A.11}$$

where A_l is the tract area we use the mean of the predictive distribution for r_{ljt} as the predicted land value. That is,

$$\begin{aligned}
\widehat{r}_{ljt} &= \int \exp(r_{ljt}) p(r_{ljt}|data, X_{ljt}^{**}, Z_{ljt}^{**}) dr_{ljt} \\
&= \int \int \exp(r_{ljt}) p(r_{ljt}|data, X_{ljt}^{**}, Z_{ljt}^{**}, \gamma_j) p(\gamma_j|data) dr_{ljt} d\gamma_j \\
&= \exp\left(Z_{ljt}^{**'} m_{\gamma,j}(\widehat{\theta}) + X_{ljt}^{**'}\widehat{\beta} + 1/2\widehat{\sigma}_e^2 + 1/2 Z_{ljt}^{**'} V_{\gamma,j}(\widehat{\theta}) Z_{ljt}^{**'} \right)
\end{aligned} \tag{A.12}$$

where the last two terms are due to the log-normal correction. We can also estimate values for cities with no observed land sales using only the prior.

Since our land data is incomplete, some land characteristics such as lot sizes and planned uses (a subvector of X_{ljt}^{**}) are unknown at the tract centroid. Therefore, we predict these characteristics based on what we do know of the land, namely its location. To do this, we decompose the predicted land value in the following manner:

$$\begin{aligned}
\widehat{r}_{ljt} &= \int \exp(r_{ljt}) p(r_{ljt}|data, X^{**}_{ljt}, Z^{**}_{ljt}) dr_{ljt} \\
&= \int\int \exp(r_{ljt}) p(r_{ljt}|data, X^{**}_{ljt}, Z^{**}_{ljt}, \gamma_j) p(\gamma_j, X^{**}_{ljt}|data, Z^{**}_{ljt}) dr_{ljt} d\gamma_j dX^{**}_{ljt} \\
&= \int\int \exp(r_{ljt}) p(r_{ljt}|data, X^{**}_{ljt}, Z^{**}_{ljt}, \gamma_j) p(\gamma_j|data) p(X^{**}_{ljt}|data, Z^{**}_{ljt}) dr_{ljt} d\gamma_j dX^{**}_{ljt} \\
&= \exp\left(Z^{**\prime}_{ljt} m_{\gamma,j}(\widehat{\theta}) + 1/2\widehat{\sigma}^2_e + 1/2 Z^{**\prime}_{ljt} V_{\gamma,j}(\widehat{\theta}) Z^{**\prime}_{ljt}\right) \int \exp\left(X^{**\prime}_{ljt}\widehat{\beta}\right) p(X^{**}_{ljt}|data, Z^{**}_{ljt}) dX^{**}_{ljt}
\end{aligned} \tag{A.13}$$

where the uncertainty about the unobserved land characteristic at the tract centroid is captured by the predictive distribution function of X^{**}_{ljt} in the last integral. We construct a model for each unobserved element in X^{**}_{ljt} using observed characteristics of the tract l in city j. More specifically, s-th element in $X^{**}_{s,ljt}$ is modeled as

$$X^{**}_{s,ljt} = \alpha^x_{s,j} + \delta^x_{s,j} D_{lj} + \gamma_s C_{lj} + e_{s,ljt}, \quad e_{s,ljt} \sim i.i.d.N(0, \sigma^2_s) \tag{A.14}$$

where D_{lj} is the distance metric based on the distance between the tract centroid and the city center, and C_{lj} is log distance to coast from the tract centroid. Then, we replace unobserved elements in X^{**}_{ljt} in equation A.13 with their predicted values.

This technique is based on a similar but simpler version of the hierarchical model used for land prices. The intercept and coefficient on the distance to the city center are allowed to vary across MSAs, but using only an affine function, as opposed to a quartic polynomial. The coefficient on the distance to the coast is fixed.

Because these coefficients are not known, we estimate them using the observed transaction data with the similar prior specification and assumption employed for the estimation of model for the land price. More specifically, the prior distribution for city-specific parameters $\alpha^x_{s,j}$ and $\delta^x_{s,j}$ follow a multivariate normal distribution. The mean vector is an affine function of each city's urban area and the variance-covariance matrix is allowed to have non-zero off-diagonal elements. We impose similar exogeneity assumptions for $\alpha^x_{s,j}$, $\delta^x_{s,j}$, and $e_{s,ljt}$. Lastly, we assume that each element in X^{**}_{ljt} are correlated only through observed tract characteristics D_{lj} and C_{lj} (equation A.14). Because estimation and prediction for the land price and land characteristics are performed conditional on distance variables, we do not assume any specific distributional form for observed distance variables D_{ij} and C_{ij}. However, we assume that the marginal density of D_{ij} puts non-zero positive value on the entire MSA area. This last assumption implies that if we do not have a transaction observation at a specific census tract, this missingness is completely random and we would eventually collect observations from this tract as the sample size goes to infinity.

B.4 Cross-validation

Cross-validation techniques help to determine the most appropriate econometric specification and evaluate the effectiveness of the shrinkage model. We design a pseudo out-of-sample prediction exercise that quantifies the potential gains or losses from different models. For this exercise we take cities that have at least 50 observations per year for at least two years This leads to 58 cities with 55,155 total observations. Then, for each city j,

1. Randomly choose n_{hold} observations out of n_{jt} observations for each time $t = 2005, 2006, ..., 2010$ in city j. We keep those $6 * n_{hold}$ observations as well as the remaining sample of data from

other cities.

2. Estimate each of models using the method described in subsection B.1

3. Generate predictions for sample held out in step 1 for city j based on the method in subsection B.2

4. Compute and store the prediction error for this hold-out samples. $\{e_{j,r,1}, e_{j,r,2}, ..., e_{j,r,(n_{jt}-n_{hold})}\}$ (forecast errors are defined as predicted minus actual).

5. Repeat Step 1 – Step 4 for $r = 1, 2, ..., R$.

6. Repeat Step 1 – Step 5 for each city $j = 1, , J$.

7. Compute aggregated out-of-sample prediction evaluation statistics. For example, the MSE for the city j is computed as

$$MSE(j) = \frac{1}{R \times (n_{j,t} - n_{hold})} \sum_{r=1}^{R} \sum_{i=1}^{(n_{jt}-n_{hold})} e^2_{r,j,i} \tag{A.15}$$

where we set $R = 30$. We perform for $n_{hold} = 3$ (small sample size) and $n_{hold} = 30$ (moderate sample size) for each city. About 35% of MSAs in our sample have observations less than equal to 18 observations (which is approximately 3 per year in our data set) and about 81% of MSAs in our sample have observations less than equal to 180 (which is approximately 30 per year in our data set). We report average $MSE(j)$ over $j = 1, 2, ...58$.

Unshrunken Estimator The unshrunken estimates are based on the fixed effect estimation. The estimator is defined as $\widehat{\gamma}_j = (Z_j'Z_j)^{-1}(Z_j'(\ln r_j - X_j\beta)$ and used in Equation A.5.

Table A.1: Estimated Coefficients on Covariates in Preferred Specification

Covariate	Estimated Coefficient	Standard Error	t-statistic	p-value
Log Lot Size	-0.543	0.0037	-146.134	0.000
(Log Lot Size Squared)/100	-3.053	0.1592	-19.176	0.000
(Log Lot Size Cubed)/1000	3.601	0.2498	14.415	0.000
Log Distance to Coast	-0.052	0.0043	-12.196	0.000
Planned Use:				
None Listed	-0.182	0.0112	-16.193	0.000
Commercial	-0.380	0.0599	-6.354	0.000
Industrial	-0.346	0.0141	-24.578	0.000
Retail	0.255	0.0134	18.963	0.000
Single Family	0.003	0.0133	0.202	0.840
Multifamily	-0.139	0.0198	-7.055	0.000
Office	0.046	0.0148	3.129	0.002
Apartment	0.288	0.0196	14.713	0.000
Hold for Development	-0.073	0.0118	-6.171	0.000
Hold for Investment	-0.283	0.0195	-14.523	0.000
Mixed Use	0.250	0.0265	9.438	0.000
Medical	0.171	0.0355	4.810	0.000
Parking	0.076	0.0373	2.044	0.041

This table reports the coefficients on the covariates from the preferred specification in table 1 from the main body of the text, which applies shrinkage to a model with a quartic polynomial in log distance to the city center plus one mile.

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
1	New York, NY	749	1,603	26,139	123,335	5,264	22.3	2,524.4
2	Jersey City, NJ	47	43	7,667	9,554	3,305	8.8	98.8
3	Honolulu, HI	198	56	4,357	16,256	3,290	7.0	416.3
4	San Francisco, CA	300	152	8,722	25,446	3,239	9.3	622.8
5	Los Angeles-Long Beach, CA	1,359	1,760	3,709	16,801	2,675	5.5	2,326.8
6	Orange County, CA	494	233	3,163	3,208	2,595	1.3	820.5
7	San Jose, CA	305	217	2,580	3,552	2,347	1.6	458.3
8	Miami, FL	372	1,233	3,052	4,478	1,794	3.2	427.5
9	Stamford-Norwalk, CT	179	19	2,753	2,740	1,505	3.2	172.4
10	Bergen-Passaic, NJ	316	79	1,957	4,145	1,423	3.7	287.7
11	Oakland, CA	495	132	2,648	5,447	1,412	3.3	447.1
12	Fort Lauderdale, FL	372	741	2,417	3,572	1,336	3.1	318.0
13	Seattle-Bellevue-Everett, WA	782	1,626	2,741	9,930	1,317	10.1	658.6
14	West Palm Beach-Boca Raton, FL	398	321	2,188	5,990	1,305	5.3	332.8
15	Santa Barbara-Santa Maria-Lompoc, CA	159	29	2,345	2,511	1,237	2.8	126.2
16	Washington, DC-MD-VA-WV	1,458	1,840	3,548	36,913	1,214	32.6	1,133.0
17	San Luis Obispo-Atascadero-Paso Robles, CA	91	43	1,416	1,563	1,174	1.6	68.4
18	Santa Cruz-Watsonville, CA	72	12	2,007	2,279	1,163	4.3	53.3
19	San Diego, CA	803	957	2,488	10,081	1,073	8.7	551.0
20	Nassau-Suffolk, NY	850	396	1,540	800	931	0.8	506.4
21	Newark, NJ	567	142	2,059	5,436	872	5.0	316.7
22	Las Vegas, NV-AZ	317	2,553	1,193	1,841	849	2.4	172.4

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
23	Naples, FL	145	78	791	1,081	738	1.5	68.5
24	Ventura, CA	202	131	1,048	1,537	692	2.4	89.7
25	Portland-Vancouver, OR-WA	527	1,191	777	6,063	679	11.5	228.9
26	Chicago, IL	2,035	3,511	1,455	37,632	663	35.1	863.3
27	Boston, MA-NH	1,295	122	1,243	8,457	600	9.8	497.5
28	Santa Rosa, CA	144	153	1,034	956	590	2.2	54.3
29	Anchorage, AK	94	21	851	490	572	1.3	34.4
30	Provo-Orem, UT	105	47	499	963	568	2.1	38.2
31	Salt Lake City-Ogden, UT	411	145	482	1,228	557	2.2	146.3
32	Denver, CO	536	2,015	828	7,586	539	18.6	185.1
33	Vallejo-Fairfield-Napa, CA	129	146	786	984	539	2.4	44.3
34	Tacoma, WA	308	539	570	2,427	530	5.6	104.4
35	Sarasota-Bradenton, FL	260	601	893	975	514	2.1	85.6
36	Providence-Fall River-Warwick, RI-MA	439	62	1,194	2,139	508	7.4	142.7
37	Panama City, FL	101	41	815	385	502	0.7	32.6
38	Baltimore, MD	858	802	969	2,281	501	4.1	275.2
39	Bridgeport, CT	200	26	837	1,581	500	3.5	63.9
40	Salinas, CA	101	12	814	1,023	490	2.6	31.6
41	Minneapolis-St. Paul, MN-WI	1,026	846	613	3,323	486	6.4	318.8
42	Middlesex-Somerset-Hunterdon, NJ	424	101	828	1,302	482	3.1	130.9
43	Fort Walton Beach, FL	86	14	300	930	478	2.4	26.3
44	Reno, NV	125	57	530	1,150	472	4.1	37.9

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	*Land Values - $000s/Acre* Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
45	Yolo, CA	34	50	624	640	468	1.5	10.1
46	Barnstable-Yarmouth, MA	188	3	387	1,090	466	3.0	56.0
47	Fort Myers-Cape Coral, FL	240	294	593	345	465	0.7	71.4
48	Gary, IN	285	111	468	2,428	463	8.4	84.5
49	Fort Pierce-Port St. Lucie, FL	180	71	475	657	463	1.9	53.4
50	Tampa-St. Petersburg-Clearwater, FL	957	1,220	1,144	3,037	454	7.5	278.1
51	Lowell, MA-NH	161	12	544	1,056	453	3.1	46.6
52	Phoenix-Mesa, AZ	897	5,946	370	3,529	452	8.4	259.4
53	Charleston-North Charleston, SC	238	214	498	2,569	446	11.0	67.8
54	Sacramento, CA	412	448	602	2,121	442	4.7	116.7
55	Orlando, FL	666	1,612	739	3,191	431	6.9	183.9
56	Monmouth-Ocean, NJ	524	124	642	2,044	425	5.4	142.5
57	Albuquerque, NM	281	114	413	635	418	1.5	75.0
58	Charlottesville, VA	47	4	728	589	415	2.2	12.4
59	Punta Gorda, FL	98	63	648	963	406	2.6	25.4
60	Atlantic-Cape May, NJ	174	37	538	1,298	406	4.1	45.2
61	Wilmington, NC	139	50	420	830	402	2.2	35.8
62	Stockton-Lodi, CA	130	163	531	423	399	1.0	33.1
63	Colorado Springs, CO	199	892	409	830	396	2.4	50.5
64	New Haven-Meriden, CT	270	43	658	1,745	396	6.1	68.4
65	Modesto, CA	120	142	407	707	388	2.3	29.9
66	Boulder-Longmont, CO	91	183	758	462	387	1.9	22.5

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
67	Danbury, CT	160	23	426	1,003	368	4.3	37.8
68	Bremerton, WA	130	18	465	856	367	2.7	30.5
69	Madison, WI	130	239	468	2,815	365	13.9	30.4
70	Philadelphia, PA-NJ	1,725	859	939	13,254	362	29.4	400.1
71	Myrtle Beach, SC	97	84	507	1,000	360	4.1	22.4
72	Burlington, VT	68	5	790	773	358	3.7	15.7
73	Trenton, NJ	127	35	432	800	354	2.7	28.9
74	Boise City, ID	158	106	294	601	349	1.9	35.3
75	Lawrence, MA-NH	236	29	410	1,178	344	5.1	51.9
76	Reading, PA	124	36	324	529	342	2.0	27.1
77	Visalia-Tulare-Porterville, CA	104	32	614	557	340	3.7	22.7
78	La Crosse, WI-MN	44	21	295	488	339	2.5	9.6
79	Norfolk-Virginia Beach-Newport News, VA-NC	554	392	377	1,375	337	5.0	119.4
80	Monroe, LA	78	7	360	605	336	3.3	16.8
81	Tallahassee, FL	125	52	474	1,001	335	5.6	26.9
82	Iowa City, IA	36	9	423	428	334	2.5	7.6
83	Salem, OR	109	54	356	868	334	3.4	23.2
84	Olympia, WA	105	250	455	543	333	2.5	22.5
85	New Orleans, LA	364	66	672	1,690	332	5.9	77.5
86	Bellingham, WA	57	19	286	514	331	2.4	12.2
87	Springfield, MA	252	28	523	1,336	328	5.4	52.9
88	New Bedford, MA	72	14	503	597	326	3.1	15.1

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
89	Lexington, KY	138	29	345	564	320	1.9	28.2
90	Spokane, WA	160	55	603	1,389	318	6.4	32.6
91	Jacksonville, FL	497	793	559	776	316	2.3	100.6
92	Riverside-San Bernardino, CA	971	2,452	433	637	315	1.5	195.5
93	El Paso, TX	206	94	321	399	313	1.2	41.3
94	Daytona Beach, FL	225	93	539	368	312	1.2	45.0
95	Portsmouth-Rochester, NH-ME	133	13	291	581	310	2.6	26.4
96	Portland, ME	120	25	1,399	869	309	3.6	23.8
97	Grand Junction, CO	60	21	343	565	307	2.8	11.8
98	Nashville, TN	580	455	499	1,499	306	4.7	113.6
99	Dallas, TX	1,057	811	454	2,774	305	10.1	206.4
100	Richland-Kennewick-Pasco, WA	95	27	273	357	300	1.7	18.3
101	Wilmington-Newark, DE-MD	215	107	445	607	298	3.1	40.9
102	Tucson, AZ	325	1,749	320	914	296	3.3	61.5
103	Columbus, GA-AL	114	11	250	620	294	3.3	21.5
104	Medford-Ashland, OR	66	12	379	465	293	2.5	12.4
105	Austin-San Marcos, TX	423	384	434	3,054	293	12.8	79.3
106	Melbourne-Titusville-Palm Bay, FL	255	420	688	353	293	1.3	47.8
107	Gainesville, FL	79	34	384	527	292	3.8	14.8
108	Merced, CA	61	64	319	455	288	2.1	11.2
109	Chattanooga, TN-GA	303	51	387	1,367	283	5.8	54.8
110	Sioux Falls, SD	49	17	306	372	283	2.5	8.9

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
111	Santa Fe, NM	78	7	335	539	282	2.2	14.1
112	Green Bay, WI	83	49	289	340	282	2.3	15.1
113	Greenville, NC	47	9	259	460	279	3.5	8.4
114	Yuba City, CA	42	13	890	625	278	6.6	7.4
115	Raleigh-Durham-Chapel Hill, NC	532	782	497	627	276	2.5	94.2
116	Waterbury, CT	125	9	243	437	275	2.2	21.9
117	Bakersfield, CA	161	64	250	625	272	2.0	28.0
118	Houston, TX	1,341	1,143	423	2,813	272	9.4	233.1
119	Joplin, MO	72	8	255	450	271	2.7	12.5
120	Detroit, MI	1,426	679	456	2,321	270	6.6	246.6
121	Las Cruces, NM	88	18	240	430	270	2.3	15.2
122	Fort Collins-Loveland, CO	91	344	417	348	270	1.4	15.7
123	Fresno, CA	215	137	247	453	266	1.8	36.7
124	Cincinnati, OH-KY-IN	645	637	441	1,656	266	6.7	109.8
125	Abilene, TX	49	3	356	337	266	2.5	8.4
126	Fayetteville-Springdale-Rogers, AR	135	43	356	293	263	1.7	22.7
127	Eugene-Springfield, OR	92	36	413	598	262	4.1	15.4
128	Worcester, MA-CT	248	56	454	1,918	261	11.2	41.3
129	Lawrence, KS	26	6	266	293	252	2.1	4.3
130	Atlanta, GA	2,105	5,229	402	1,750	251	5.5	338.6
131	Fargo-Moorhead, ND-MN	46	13	470	274	251	1.7	7.4
132	Omaha, NE-IA	237	118	633	1,147	251	4.7	38.0

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	*Land Values - $000s/Acre* Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
133	Cleveland-Lorain-Elyria, OH	745	416	545	713	251	2.4	119.7
134	Greeley, CO	48	320	302	359	246	2.1	7.5
135	Huntsville, AL	179	29	190	519	244	2.3	28.0
136	Lincoln, NE	78	24	258	430	243	3.5	12.1
137	Billings, MT	53	25	297	319	243	2.5	8.2
138	Harrisburg-Lebanon-Carlisle, PA	243	89	334	1,084	242	7.7	37.7
139	Manchester, NH	97	23	230	559	240	3.9	14.9
140	Fort Worth-Arlington, TX	693	506	313	566	239	2.3	105.8
141	Louisville, KY-IN	413	126	279	650	233	2.7	61.6
142	Baton Rouge, LA	292	99	308	907	228	3.6	42.7
143	Janesville-Beloit, WI	56	15	277	301	226	3.1	8.1
144	McAllen-Edinburg-Mission, TX	318	61	400	398	226	2.6	45.9
145	Asheville, NC	126	41	318	499	226	3.0	18.1
146	Columbus, OH	512	671	614	1,238	222	5.5	72.8
147	Tulsa, OK	332	245	323	744	222	3.0	47.1
148	Bloomington-Normal, IL	39	10	193	264	220	2.8	5.5
149	Milwaukee-Waukesha, WI	542	399	313	821	219	3.8	76.0
150	Dubuque, IA	31	4	210	266	219	2.3	4.4
151	Anniston, AL	77	4	214	397	218	2.8	10.8
152	Waterloo-Cedar Falls, IA	53	12	229	298	215	2.5	7.3
153	Rocky Mount, NC	52	12	292	299	215	1.9	7.1
154	Roanoke, VA	111	23	208	442	214	2.9	15.2

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

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Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
155	Nashua, NH	96	3	147	426	212	3.1	13.0
156	Columbia, MO	54	3	206	333	212	2.8	7.3
157	Hagerstown, MD	49	28	348	518	212	9.5	6.6
158	Richmond-Petersburg, VA	441	399	293	1,509	212	8.4	59.7
159	Brockton, MA	148	22	362	528	212	3.3	20.1
160	Galveston-Texas City, TX	116	39	267	445	211	2.1	15.7
161	Allentown-Bethlehem-Easton, PA	264	85	281	348	211	2.3	35.6
162	Missoula, MT	36	4	374	311	210	2.6	4.9
163	Lake Charles, LA	99	14	206	441	209	3.4	13.3
164	Decatur, IL	50	2	239	331	209	3.4	6.7
165	Champaign-Urbana, IL	58	22	262	338	207	4.1	7.6
166	Savannah, GA	128	64	337	370	204	1.9	16.7
167	Kansas City, MO-KS	698	477	342	565	202	2.4	90.4
168	St. Louis, MO-IL	979	364	337	700	200	3.1	125.5
169	Little Rock-North Little Rock, AR	244	110	305	528	200	3.0	31.2
170	Decatur, AL	39	5	533	402	196	4.3	5.0
171	Birmingham, AL	421	148	238	298	196	1.4	52.9
172	Rochester, MN	43	7	189	253	196	3.1	5.4
173	Steubenville-Weirton, OH-WV	54	1	122	268	195	2.3	6.7
174	Indianapolis, IN	649	193	274	858	195	3.8	80.9
175	Hamilton-Middletown, OH	124	151	372	96	195	0.3	15.4
176	Auburn-Opelika, AL	62	5	233	267	195	1.8	7.8

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
177	York, PA	180	47	176	460	194	2.5	22.4
178	Laredo, TX	47	2	255	300	194	2.5	5.9
179	Dayton-Springfield, OH	382	116	317	777	194	5.1	47.4
180	Flagstaff, AZ-UT	35	7	294	230	194	1.9	4.4
181	Springfield, MO	124	43	261	487	194	4.0	15.3
182	San Antonio, TX	468	348	224	710	192	3.7	57.6
183	Pensacola, FL	246	102	317	669	192	3.6	30.3
184	Columbia, SC	270	139	237	871	190	6.5	32.8
185	Redding, CA	78	8	150	289	189	2.0	9.4
186	Hartford, CT	616	101	672	1,139	188	6.3	74.1
187	Lancaster, PA	229	57	176	597	188	4.7	27.5
188	Fayetteville, NC	156	25	476	253	184	1.7	18.4
189	Greensboro–Winston Salem–High Point, NC	602	438	297	274	183	1.6	70.4
190	Knoxville, TN	400	193	265	496	181	2.5	46.3
191	Houma, LA	93	4	102	474	180	3.1	10.7
192	Jacksonville, NC	94	6	134	368	180	2.4	10.8
193	St. Cloud, MN	45	17	331	252	179	2.3	5.1
194	Newburgh, NY-PA	169	54	206	504	178	3.1	19.2
195	Yakima, WA	74	15	182	289	178	1.9	8.4
196	Tuscaloosa, AL	76	16	252	349	177	3.3	8.6
197	Bangor, ME	38	5	339	347	176	3.4	4.3
198	Biloxi-Gulfport-Pascagoula, MS	172	30	163	424	173	3.6	19.0

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
199	Kenosha, WI	64	58	604	161	173	1.2	7.1
200	Lakeland-Winter Haven, FL	247	561	324	283	172	2.0	27.2
201	Duluth-Superior, MN-WI	81	22	344	133	172	1.7	8.9
202	Ann Arbor, MI	231	136	293	1,227	172	12.3	25.4
203	New London-Norwich, CT-RI	166	31	299	296	171	1.7	18.2
204	Clarksville-Hopkinsville, TN-KY	96	60	213	274	171	2.4	10.5
205	Dutchess County, NY	158	33	588	804	170	6.6	17.2
206	Pine Bluff, AR	35	2	232	215	167	2.2	3.8
207	Springfield, IL	94	11	430	335	166	4.3	10.0
208	Cumberland, MD-WV	41	6	145	283	166	2.5	4.3
209	Grand Rapids-Muskegon-Holland, MI	435	121	243	537	166	4.9	46.2
210	Vineland-Millville-Bridgeton, NJ	72	11	410	261	166	3.7	7.6
211	Lafayette, IN	61	13	190	192	164	1.5	6.4
212	Jackson, MS	192	43	191	753	164	6.1	20.2
213	Eau Claire, WI	63	30	123	225	164	1.7	6.6
214	Buffalo-Niagara Falls, NY	395	104	616	1,157	162	8.6	41.1
215	Memphis, TN-AR-MS	423	173	328	572	162	4.1	43.9
216	Waco, TX	73	14	185	227	161	2.2	7.6
217	Oklahoma City, OK	391	395	285	280	161	1.5	40.3
218	Bismarck, ND	34	22	155	153	161	1.5	3.5
219	Johnson City-Kingsport-Bristol, TN-VA	273	28	169	284	160	2.2	28.0
220	Brownsville-Harlingen-San Benito, TX	125	52	263	159	159	0.8	12.8

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
221	Canton-Massillon, OH	189	40	220	264	159	2.3	19.2
222	Des Moines, IA	158	99	238	776	158	5.5	16.1
223	Augusta-Aiken, GA-SC	243	66	228	250	158	1.6	24.6
224	South Bend, IN	126	12	118	335	157	3.3	12.7
225	Dover, DE	54	7	151	253	157	2.5	5.4
226	Yuma, AZ	54	12	215	355	156	3.2	5.4
227	Pittsburgh, PA	1,003	240	433	1,772	156	10.6	100.0
228	Amarillo, TX	85	27	173	215	155	2.2	8.4
229	Terre Haute, IN	54	4	200	237	151	2.1	5.2
230	Akron, OH	337	169	349	446	150	2.9	32.4
231	Texarkana, TX-Texarkana, AR	70	5	118	225	150	2.6	6.7
232	Montgomery, AL	133	33	252	487	148	4.0	12.6
233	Cedar Rapids, IA	62	33	151	216	148	2.0	5.9
234	Jonesboro, AR	41	8	194	252	148	3.1	3.9
235	Lynchburg, VA	87	13	152	258	147	1.8	8.2
236	Wichita, KS	205	54	229	298	147	2.1	19.2
237	Corpus Christi, TX	139	74	179	236	146	1.6	13.1
238	Ocala, FL	145	38	265	338	142	3.2	13.2
239	Lawton, OK	55	20	177	164	139	2.3	4.9
240	Corvallis, OR	33	3	436	226	135	3.3	2.8
241	Elmira, NY	35	9	240	147	135	1.2	3.0
242	Owensboro, KY	39	1	41	174	135	2.3	3.3

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
243	Goldsboro, NC	47	6	156	196	135	2.2	4.1
244	Racine, WI	73	80	166	197	134	1.6	6.2
245	Davenport-Moline-Rock Island, IA-IL	136	28	178	196	134	2.2	11.6
246	Mobile, AL	273	135	167	658	133	5.2	23.2
247	Greenville-Spartanburg-Anderson, SC	542	507	294	199	133	1.8	46.1
248	Sheboygan, WI	33	15	112	194	133	2.2	2.8
249	Pocatello, ID	30	7	208	122	133	1.7	2.5
250	San Angelo, TX	46	2	109	169	131	2.0	3.8
251	Lafayette, LA	165	15	118	287	130	3.0	13.8
252	Albany-Schenectady-Troy, NY	355	120	158	421	130	6.5	29.5
253	Athens, GA	79	15	189	226	129	2.6	6.6
254	Hattiesburg, MS	39	5	143	172	129	2.1	3.2
255	State College, PA	29	12	136	176	128	2.7	2.4
256	Pittsfield, MA	49	3	17	195	128	2.6	4.0
257	Evansville-Henderson, IN-KY	113	33	74	253	126	3.2	9.1
258	Brazoria, TX	110	62	225	111	125	1.4	8.7
259	Beaumont-Port Arthur, TX	165	60	140	231	124	2.2	13.1
260	Hickory-Morganton-Lenoir, NC	217	88	184	239	124	3.0	17.3
261	Topeka, KS	70	7	212	146	124	1.4	5.6
262	Syracuse, NY	236	65	221	689	124	10.4	18.6
263	Tyler, TX	64	13	162	246	123	3.7	5.1
264	Kalamazoo-Battle Creek, MI	191	31	144	275	123	3.0	15.1

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	*Land Values - $000s/Acre* Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
265	Lansing-East Lansing, MI	156	40	138	353	122	5.0	12.2
266	Gadsden, AL	61	6	71	206	120	2.3	4.7
267	Williamsport, PA	39	9	49	163	120	2.0	3.0
268	Johnstown, PA	77	5	469	352	119	5.1	5.9
269	Wichita Falls, TX	65	8	133	187	116	2.7	4.8
270	Flint, MI	230	85	245	338	115	4.0	17.0
271	Bryan-College Station, TX	49	34	165	133	114	3.2	3.6
272	Killeen-Temple, TX	111	32	140	130	113	1.5	8.0
273	Fort Wayne, IN	182	39	269	309	113	2.9	13.1
274	Erie, PA	97	29	104	217	112	2.8	7.0
275	Elkhart-Goshen, IN	86	14	328	126	110	1.8	6.0
276	Macon, GA	172	20	174	262	110	2.1	12.1
277	Binghamton, NY	81	16	188	236	108	3.7	5.6
278	Benton Harbor, MI	91	12	110	200	108	1.8	6.3
279	Scranton–Wilkes-Barre–Hazleton, PA	208	27	194	243	107	3.7	14.2
280	Florence, SC	66	12	171	211	106	3.1	4.5
281	Great Falls, MT	29	1	134	114	105	1.7	1.9
282	Rockford, IL	166	104	147	272	104	3.2	11.1
283	St. Joseph, MO	40	12	191	82	103	1.2	2.7
284	Wausau, WI	38	16	104	87	103	1.2	2.5
285	Sioux City, IA-NE	50	17	162	141	102	2.6	3.3
286	Bloomington, IN	43	3	54	128	101	2.0	2.8

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
287	Alexandria, LA	58	4	55	138	97	1.9	3.6
288	Odessa-Midland, TX	99	39	129	156	95	2.2	6.0
289	Victoria, TX	51	7	70	148	95	2.1	3.1
290	Sumter, SC	45	10	99	123	94	1.7	2.7
291	Toledo, OH	203	107	172	226	93	2.3	12.1
292	Rochester, NY	388	110	632	747	93	11.8	23.1
293	Lubbock, TX	82	45	142	209	93	2.8	4.9
294	Shreveport-Bossier City, LA	179	50	88	218	91	3.1	10.4
295	Grand Forks, ND-MN	29	3	63	164	89	2.7	1.7
296	Fort Smith, AR-OK	71	18	88	152	89	2.2	4.0
297	Rapid City, SD	33	7	79	130	88	3.0	1.9
298	Appleton-Oshkosh-Neenah, WI	109	79	105	85	88	1.2	6.2
299	Mansfield, OH	74	3	125	130	87	1.9	4.1
300	Kankakee, IL	35	9	144	134	86	3.7	1.9
301	Peoria-Pekin, IL	144	25	94	195	84	3.6	7.7
302	Florence, AL	52	4	102	130	79	3.2	2.6
303	Pueblo, CO	54	18	71	116	77	3.2	2.7
304	Dothan, AL	93	14	133	150	77	2.1	4.6
305	Lewiston-Auburn, ME	28	3	46	103	76	2.4	1.3
306	Lima, OH	63	8	43	133	75	2.7	3.0
307	Parkersburg-Marietta, WV-OH	51	3	65	77	73	1.7	2.4
308	Wheeling, WV-OH	58	4	27	130	73	2.7	2.7

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
309	Jackson, TN	44	4	40	99	73	1.9	2.0
310	Sharon, PA	33	9	45	111	67	2.4	1.4
311	Youngstown-Warren, OH	258	49	94	144	63	2.3	10.4
312	Enid, OK	24	2	75	75	62	1.8	1.0
313	Muncie, IN	44	5	26	87	60	1.8	1.7
314	Altoona, PA	45	8	76	95	58	2.8	1.7
315	Charlotte-Gastonia-Rock Hill, NC-SC	791	10	29	300	55	6.2	28.0
316	Danville, VA	34	5	46	67	55	1.4	1.2
317	Fitchburg-Leominster, MA	61	8	44	85	55	2.4	2.1
318	Utica-Rome, NY	89	15	103	81	55	2.2	3.1
319	Sherman-Denison, TX	34	19	40	55	54	1.6	1.2
320	Longview-Marshall, TX	84	14	289	129	52	3.8	2.8
321	Saginaw-Bay City-Midland, MI	146	41	92	103	51	2.5	4.8
322	Glens Falls, NY	33	21	46	65	45	2.6	0.9
323	Jackson, MI	57	8	49	74	38	3.0	1.4
324	Jamestown, NY	46	10	43	63	30	2.1	0.9

Table A.2: Metropolitan Land Value Indices Ranked by Average Urban Land Value per Acre, 2005-2010

				Land Values - $000s/Acre				
Rank	Metropolitan Area Name	Total Urban Area (Sq. Miles)	No. of Land Sales	Naive Model	Central	Urban Avg.	Ratio of Central to 10-Mile Values	Total Est. Urban Land Value ($ billions)
	Metropolitan Areas with no land sale observations:							
N/A	Albany, GA	66	0	-	310	200	2.6	8.4
N/A	Casper, WY	26	0	-	119	110	1.9	1.8
N/A	Charleston, WV	115	0	-	445	191	3.0	14.0
N/A	Cheyenne, WY	34	0	-	145	126	2.1	2.7
N/A	Chico-Paradise, CA	89	0	-	437	230	2.8	13.1
N/A	Huntington-Ashland, WV-KY-OH	115	0	-	448	221	3.0	16.3
N/A	Kokomo, IN	41	0	-	212	162	2.2	4.2

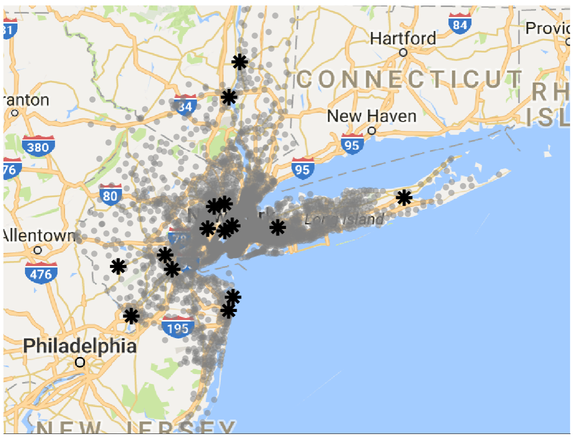
Table A.3: Comparison of Transaction-Based and Residual-Based Estimates of Land Values, 2005-2010

	Value ($000s)			*Total Value - $ billions*	
Metropolitan Area Name	Davis and Palumbo (2008) Estimate for Typical Lot	Davis and Palumbo Estimate per Estimated Acre	Our COMPS Transaction-Based (AES) Estimate per Acre	Davis and Palumbo Estimate for Residential Land	Our (AES) Estimate for All Urban Land
New York NY	345	835	5,264	890	2,524
San Francisco CA	844	3,591	3,239	464	623
Los Angeles-Long Beach CA	438	1,094	2,675	1,077	2,327
San Jose CA	666	1,681	2,347	306	458
Miami FL	241	1,103	1,794	165	428
Oakland CA	475	1,189	1,412	347	447
Seattle-Bellevue-Everett WA	251	913	1,317	197	659
Washington DC-MD-VA-WV	312	918	1,214	460	1,133
San Diego CA	414	708	1,073	319	551
Portland-Vancouver OR-WA	183	160	679	111	229
Chicago IL	108	387	663	273	863
Boston MA-NH	340	499	600	392	498
Salt Lake City-Ogden UT	87	194	557	35	146
Denver CO	91	160	539	64	185
Baltimore MD	176	210	508	69	143
Providence-Fall River-Warwick RI-MA	241	415	501	195	275
Minneapolis-St. Paul MN-WI	57	101	486	52	319
Phoenix-Mesa AZ	68	305	454	64	278
Tampa-St. Petersburg-Clearwater FL	100	284	452	109	259
Sacramento CA	160	219	442	76	117
Philadelphia PA-NJ	123	292	362	208	400
New Orleans LA	155	293	337	74	119
Norfolk-Virginia Beach-Newport News VA-	72	192	332	32	77
Riverside-San Bernardino CA	132	281	315	118	196
Dallas TX	56	90	305	58	206
Houston TX	31	136	272	38	233
Detroit MI	15	30	270	22	247
Cincinnati OH-KY-IN	30	26	266	16	110
Atlanta GA	26	25	251	31	339
Cleveland-Lorain-Elyria OH	33	46	251	25	120
Fort Worth-Arlington TX	26	41	239	14	106
Columbus OH	44	47	222	21	73
Milwaukee-Waukesha WI	69	80	219	34	76
Kansas City MO-KS	18	16	202	10	90
St. Louis MO-IL	20	19	200	17	125
Indianapolis IN	36	26	196	10	53
Birmingham AL	11	11	195	5	81
San Antonio TX	18	67	192	8	58
Hartford CT	121	429	188	34	74
Buffalo-Niagara Falls NY	25	24	162	10	41
Memphis TN-AR-MS	14	16	162	5	44
Oklahoma City OK	12	24	161	4	40
Pittsburgh PA	11	9	156	8	100
Rochester NY	17	50	93	5	23
Charlotte-Gastonia-Rock Hill NC-SC	88	61	55	38	28
Average	*152*	*392*	*722*	*147*	*352*
Standard Deviation	*183*	*626*	*983*	*224*	*511*

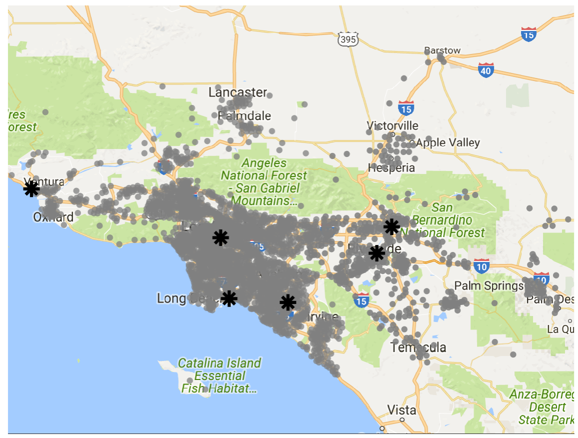
Davis and Palumbo (2008) estimates are geometric means of quarterly values from 2005q1 to 2010q4. Per-acre values calculated by dividing by an estimated average lot size, for owner-occupied units with positive reported acreage from 2011 American Housing Survey data, which were unavailable for Orange County. Total values for DP taking these times number of housing units in urbanized area as of 2000 Census, counting rented units as one half a regular unit. Davis and Palumbo estimates were downloaded from the Lincoln Land Institute website February 2017 at http://datatoolkits.lincolninst.edu/subcenters/land-values/metro-area-land-prices.asp.

Figure A.1: Geographical Distribution of Land Sales in Four Consolidated MSAs

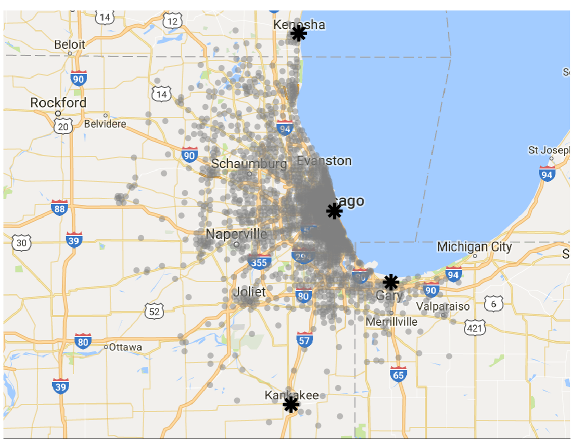
(a) New York Northern New Jersey, Long Island, NY-NJ-CT-PA



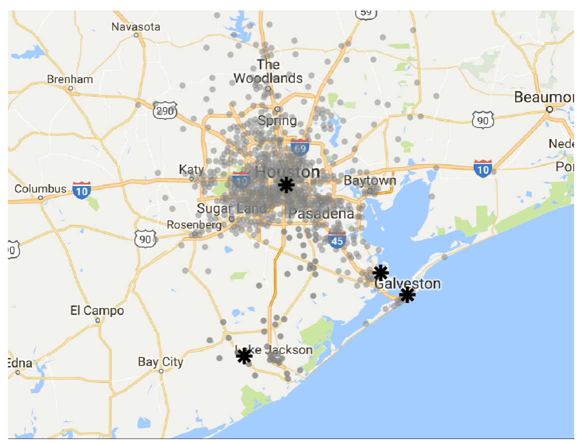
(b) Los Angeles-Riverside-Orange County CA



(c) Chicago-Gary-Kenosha IL-IN-WI



(d) Houston-Galveston-Brazoria TX



The gray dots represent land sales. The black stars represent city centers.