Motivation: Why Care about Urban Land Values?

Urban land values reflect private value of a location from:

1. Local quality of life consumption amenities (schools, sunshine)
2. Access to jobs and local productivity (Wall St, Amazon HQ2)
3. Opportunities for residential and commercial development
Motivation: Why Care about Urban Land Values?

Urban land values reflect private value of a location from:
1. Local quality of life consumption amenities (schools, sunshine)
2. Access to jobs and local productivity (Wall St, Amazon HQ2)
3. Opportunities for residential and commercial development

Land an important source of income in the economy, but how big?
- Agricultural values now appear small in comparison (Piketty, 2014)
- Urban land main source of potential revenue for land-value taxation
- Some estimates from Flow of Funds (FOF) generated negative values
Motivation: Why Care about Urban Land Values?

Urban land values reflect private value of a location from:
1. Local quality of life consumption amenities (schools, sunshine)
2. Access to jobs and local productivity (Wall St, Amazon HQ2)
3. Opportunities for residential and commercial development

Land an important source of income in the economy, but how big?
- Agricultural values now appear small in comparison (Piketty, 2014)
- Urban land main source of potential revenue for land-value taxation
- Some estimates from Flow of Funds (FOF) generated negative values

Key at unlocking what drives housing prices
- How much does geography and land-use restrictions contribute?
- What regulations hurt the most.
- Do we see quality of life benefits from land-use benefits?
We generate a measure of metropolitan land values

1. Based on directly-observed market transactions
2. Can be compared and aggregated across all U.S. metro areas.
3. Covers all urban land (not just residential) in metro areas.
4. Differs from “residual” = total - construction cost estimates.
We generate a measure of metropolitan land values

1. Based on directly-observed market transactions
2. Can be compared and aggregated across all U.S. metro areas.
3. Covers all urban land (not just residential) in metro areas.
4. Differs from “residual” = total - construction cost estimates.

Develop econometric techniques for small samples over large areas.

- Based on a monocentric-city model of land values
- Cross-validation suggests technique improves predictions
- Can be used to fill in cities with no data!
We generate a measure of metropolitan land values
1. Based on directly-observed market transactions
2. Can be compared and aggregated across all U.S. metro areas.
3. Covers all urban land (not just residential) in metro areas.
4. Differs from “residual” = total - construction cost estimates.

Develop econometric techniques for small samples over large areas.
- Based on a monocentric-city model of land values
- Cross-validation suggests technique improves predictions
- Can be used to fill in cities with no data!

Provide a measure of aggregate land values across all cities.
- Changes over time
- Consistently positive, unlike flow of funds...
Nichols, Oliner, Mulhall (2013) produce time series for 20 cities
- Market transaction measures comparable over time
- Develop technique to map values over grid
Nichols, Oliner, Mulhall (2013) produce time series for 20 cities
- Market transaction measures comparable over time
- Develop technique to map values over grid

Davis & Heathcote (2007) and Davis & Palumbo (2008): residual method
- DH: Time series since 1930s.
- DP: 45 cities comparable over space since 1980
Related Literature on Land Values

Nichols, Oliner, Mulhall (2013) produce time series for 20 cities
- Market transaction measures comparable over time
- Develop technique to map values over grid

Davis & Heathcote (2007) and Davis & Palumbo (2008): residual method
- DH: Time series since 1930s.
- DP: 45 cities comparable over space since 1980

Problem with negative values
1. DH: Negative value for all residential land in 1940
2. DP: Zero or negative value in some cities.
Related Literature on Land Values

Nichols, Oliner, Mulhall (2013) produce time series for 20 cities
- Market transaction measures comparable over time
- Develop technique to map values over grid

Davis & Heathcote (2007) and Davis & Palumbo (2008): residual method
- DH: Time series since 1930s.
- DP: 45 cities comparable over space since 1980

Problem with negative values
1. DH: Negative value for all residential land in 1940
2. DP: Zero or negative value in some cities.

Other studies use transaction data for local analyses: Haughwout (2008), Kok et al. (2014).
Overview of Talk

1. Introduction
2. Description of Transactions Data and Urban Land Area
3. Econometric Methods
4. Aggregate Urban Land Values over Time
5. Conclusion
6. Extensions
Average urban land worth $624K per acre in 2006. Total is 2.2 times GDP.

- Falls to $373K by 2009, or 1.3 times GDP
Average urban land worth $624K per acre in 2006. Total is 2.2 times GDP.
- Falls to $373K by 2009, or 1.3 times GDP

Highest central values in New York, Honolulu, San Francisco, Los Angeles
1. Central value 82 times higher than lowest five cities
2. Central value 21 times higher than value 10 miles away.
3. Smaller cities: central/10-mile ratio only 4 times.
Average urban land worth $624K per acre in 2006. Total is 2.2 times GDP.
- Falls to $373K by 2009, or 1.3 times GDP

Highest central values in New York, Honolulu, San Francisco, Los Angeles
1. Central value 82 times higher than lowest five cities
2. Central value 21 times higher than value 10 miles away.
3. Smaller cities: central/10-mile ratio only 4 times.

Measure varies considerably from “residual” measures
- For most cities our values are higher
- Less volatile over time
- Never produce negative values
Our primary data source is the CoStar COMPS database

- Arms-length market transaction between 2005 and 2010
- Only “land ” transactions with complete info, ≥ $100 an acre.
- Each property: price, lot size, address, & “proposed use”
- We geocoded them ourselves. Keep within 60 miles of center.
- After basic cleaning: 68,756 land sales.

These are commercial lots broadly defined. Median lot size is 3.5 acres versus a mean of 26 acres. Land sales occur more in the beginning: 21.7% in 2005; 11.4% in 2010. 17.6% marked for residential uses. 23.4% is being held for development or investment. 16% of the sample had no listed proposed use.
Our primary data source is the CoStar COMPS database

- Arms-length market transaction between 2005 and 2010
- Only “land” transactions with complete info, $\geq 100$ an acre.
- Each property: price, lot size, address, & “proposed use”
- We geocoded them ourselves. Keep within 60 miles of center.
- After basic cleaning: 68,756 land sales.

These are commercial lots broadly defined.

- Median lot size is 3.5 acres versus a mean of 26 acres.
- Land sales occur more in beginning: 21.7% in 2005; 11.4% in 2010.
- 17.6% marked for residential uses
- 23.4% is being held for development or investment
- 16% of the sample had no listed proposed use.
“Cities”/Metro areas definitions: 1999 OMB Metropolitan Statistical Areas (MSAs).

- Consists of counties
- Separate “Primary” MSAs, e.g. San Francisco and Oakland
- Covers 80 percent of the U.S. population

Consider only land in urban area by 2000 Census definitions.

- Block group has a min. density of 1,000 per square mile
- Contiguous with other urban block groups.

City centers to be the City Hall or Mayor's office of each city.

- Split MSA with multiple cities, e.g., Minneapolis-St. Paul.
- Land parcels assigned to closest city center
New York Northern New Jersey, Long Island

Gray dots: Land sales
Black stars: City centers
Los Angeles-Riverside-Orange County

Gray dots: Land sales
Black stars: City centers
Chicago-Gary-Kenosha

Gray dots: Land sales
Black stars: City centers
Houston-Galveston-Brazoria

Gray dots: Land sales
Black stars: City centers
Two major obstacles to constructing a cross-metropolitan land value index from observed transactions data.

1. Observed transactions are not a random sample of all parcels in a city. (Covariates)

2. We observe few sales in many smaller metro areas, reducing the reliability of the estimates. (Shrinkage Estimation)
For a lot $i$ in city $j$ at time $t$, the land value $r_{ijt}$:

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

- Following the monocentric city model, we take each city $j$ as having a fixed center, with coordinates $z_{j}^c$.

- Land values, $r$, vary according to a city-specific polynomial in the distance metric, $D(z_{ij}, z_{j}^c)$, between plot $i$’s coordinates $z_{ij}$ and the center.

- City-center values $\alpha_{jt}$ may vary by year, $t$; coefficients $\delta_{jk}$, which determine the shape of the value-distance gradient, are held constant over time due to limited sample sizes:

- Controls $X_{ijt}$ include proposed use, lot size, distance from the coast.

- The idiosyncratic error term, $e_{ijt}$, follows an independent and identically distributed normal distribution.
Land Value Gradient Estimates for the Houston

Estimated Distance Polynomial with $D = \ln(1 + \text{mileage})$
For a lot $i$ in city $j$ at time $t$, the land value $r_{ijt}$:

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

To deal with limited sample sizes we develop a hierarchical model.

- It “shrinks” metro-level estimates ($\alpha_{jt}, \delta_{j1}, ... \delta_{jK}$) towards a national average function.
- This function target depends on each city’s urban area, $A_j$.
  - e.g., **Land values of a large city** with a smaller number of transactions are shrunken toward values other large cities.
  - e.g., **Land values of a small city**, often have few transactions per year: sometimes none at all! Can still use average of city with similar footprint.
  - The weaker data information, the stronger shrinkage (for each $j$).

We do this by placing a prior on ($\alpha_{jt}, \delta_{j1}, ... \delta_{jK}$).
Shrinkage Estimation – Time-varying component

For a lot \( i \) in city \( j \) at time \( t \), the land value \( r_{ijt} \):

\[
\ln r_{ijt} = \alpha_{jt} + \sum_{k=1}^{K} \delta_{jk} \left[ D(z_{ij}, z_{j}^c) \right]^k + X_{ijt}\beta + e_{ijt}, \quad e_{ijt} \sim \text{i.i.d. } N(0, \sigma^2_e).
\]

We begin by decomposing the central value \( \alpha_{jt} \) into two components,

\[
\alpha_{jt} = \alpha_j + \alpha_{jt}^* \]

where \( \alpha_{jt}^* \) is normalized to zero.

Time-varying component follows the prior \( \alpha_{jt}^* \sim N(\tau_t, \sigma^2_t) \).

- Time-varying components of central values vary across cities and time
- City-level trend fluctuates around the national-level trend, \( \tau_t \).
- Heterogeneity in MSA-level departures changes over time through \( \sigma^2_t \).
For a lot $i$ in city $j$ at time $t$, the land value $r_{ijt}$:

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

Time-invariant component, $(\alpha_j, \delta_j')$ where $\delta_j = [\delta_{j1} \delta_{j2} \cdots \delta_{jK}]'$, follows the prior:

$$\begin{bmatrix} \alpha_j \\
\delta_j 
\end{bmatrix} = \begin{bmatrix} a_0 & a_1 \\
d_0 & d_1 
\end{bmatrix} \begin{bmatrix} 1 \\
\ln A_j \n\end{bmatrix} + \begin{bmatrix} e_{\alpha,j} \\
\mathbf{e}_{\delta,j} \n\end{bmatrix}$$

where

$$\begin{bmatrix} e_{\alpha,j} \\
\mathbf{e}_{\delta,j} \end{bmatrix} \sim \text{i.i.d.} \ N\left(\begin{bmatrix} 0 \\
0 \n\end{bmatrix}, \begin{bmatrix} \Sigma_{\alpha\alpha} & \Sigma_{\alpha\delta} \\
\Sigma_{\delta\alpha} & \Sigma_{\delta\delta} \n\end{bmatrix} \right)$$
For a lot $i$ in city $j$ at time $t$, the land value $r_{ijt}$:

$$\ln r_{ijt} = \sum_{t=2005}^{2010} \alpha_{jt} + \sum_{k=1}^{K} \delta_{jk} [D(z_{ij}, z^c_{j})]^{k} + X_{ijt} \beta + e_{ijt}, \quad e_{ijt} \sim \text{i.i.d. } N(0, \sigma^2_e).$$

Prior constructs a “metacity” described by the parameters $a_0, a_1, \delta_0$, and $\delta_0$.

- Provides the land rent gradient typical of a city with area $A_j$.
- Larger cities typically have higher central land values.
- Values descend and dovetail with non-urban values at different rates.
- Allows for a full covariance matrix between the random components of the intercept and distance coefficients, $e_{\alpha,j}$ and $e_{\delta,j}$. 
Shrinkage Estimation – Implication

If all other parameters are known and $\alpha^*_jt = 0$, the best linear unbiased predictor (BLUP) for $[\alpha_j, \delta_j]'$ is a weighted average between metacity (prior mean) and conventional metro-level (fixed effect) estimates, $[\hat{\alpha}_j, \hat{\delta}_j]'$:

$$
\begin{bmatrix}
\tilde{\alpha}_j \\
\tilde{\delta}_j
\end{bmatrix} = W_j \begin{bmatrix} a_0 & a_1 \\ d_0 & d_1 \end{bmatrix} \begin{bmatrix} 1 \\ \ln A_j \end{bmatrix} + (I - W_j) \begin{bmatrix} \hat{\alpha}_j \\
\hat{\delta}_j
\end{bmatrix}
$$

(1)

where the weighting matrix $W_j$ accounts for the amount of shrinkage in city $j$.

This shrinkage term

- falls with the number of observations in city $j$ (i.e., more weight on data)
- rises with the uncertainty in the prior ($\Sigma\alpha\alpha$, $\Sigma\delta\alpha$, $\Sigma\delta\delta$) and the idiosyncratic error term, $\sigma^2_e$ (i.e., less weight on data)

We estimate metacity parameters $(a_0, a_1, d_0, d_1)$ and their variance ($\Sigma\alpha\alpha$, $\Sigma\delta\alpha$, $\Sigma\delta\delta$) so that the estimated Metacity is the national average.
Estimating the Empirical Full Model

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

\[
\alpha_{jt} = \alpha_j + \alpha_{jt}^*, \quad \alpha_{jt}^* \sim N(\tau_t, \sigma_t^2)
\]

\[
\begin{bmatrix}
\alpha_j \\
\delta_j
\end{bmatrix}
= \begin{bmatrix}
a_0 & a_1 \\
d_0 & d_1
\end{bmatrix}
\begin{bmatrix}
1 & \\
\ln A_j
\end{bmatrix}
+ \begin{bmatrix}
e_{\alpha,j} \\
e_{\delta,j}
\end{bmatrix}
\]

\[
\begin{bmatrix}
e_{\alpha,j} \\
e_{\delta,j}
\end{bmatrix}
\sim \text{i.i.d. } N\left(\begin{bmatrix}0 \\
0\end{bmatrix}, \begin{bmatrix}\Sigma_{\alpha\alpha} & \Sigma_{\alpha\delta} \\
\Sigma_{\delta\alpha} & \Sigma_{\delta\delta}\end{bmatrix}\right)
\]

We estimate fixed parameters \((\beta, a_0, a_1, d_0, d_1, \tau_{2006}, \ldots, \tau_{2010})\) and variance parameters \((\sigma^2, \Sigma_{\alpha\alpha}, \Sigma_{\alpha\delta}, \Sigma_{\delta\delta}, \sigma_{2006}^2, \ldots, \sigma_{2010}^2)\). Adopt an empirical Bayes-type approach: parameters are found by maximizing the marginal likelihood with a flat (improper) prior.
We perform out-of-sample prediction exercise:

- Fix a number of MSAs & randomly retain a few observations per year.

- Use those few observations & model estimates from other MSAs to predict the values of the non-retained observations.

- Forecast error is the difference between the predicted price and the actual price of these non-retained observations.

- Repeat above multiple times to approximate the mean squared error (MSE) and we use it to assess the model.
<table>
<thead>
<tr>
<th>Model Specification</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
</table>

**Panel A: 3 observations per city-year**

<table>
<thead>
<tr>
<th>Metric</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Squared Error</td>
<td>1.640</td>
<td>1.143</td>
<td>0.939</td>
<td>0.938</td>
<td>0.936</td>
<td>0.936</td>
<td>0.935</td>
</tr>
<tr>
<td>Bias</td>
<td>-0.004</td>
<td>0.013</td>
<td>0.016</td>
<td>0.013</td>
<td>0.013</td>
<td>0.013</td>
<td>0.013</td>
</tr>
<tr>
<td>Variance</td>
<td>1.586</td>
<td>1.105</td>
<td>0.910</td>
<td>0.909</td>
<td>0.907</td>
<td>0.906</td>
<td>0.905</td>
</tr>
</tbody>
</table>

**Panel B: 30 observations per city-year**

<table>
<thead>
<tr>
<th>Metric</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Squared Error</td>
<td>1.449</td>
<td>0.912</td>
<td>0.904</td>
<td>0.902</td>
<td>0.898</td>
<td>0.897</td>
<td>0.896</td>
</tr>
<tr>
<td>Bias</td>
<td>-0.004</td>
<td>-0.003</td>
<td>0.001</td>
<td>0.000</td>
<td>0.001</td>
<td>0.001</td>
<td>0.000</td>
</tr>
<tr>
<td>Variance</td>
<td>1.441</td>
<td>0.907</td>
<td>0.899</td>
<td>0.898</td>
<td>0.893</td>
<td>0.892</td>
<td>0.891</td>
</tr>
</tbody>
</table>

**Shrunken?**

- No
- Yes

**Polynomial Order - Distance**

- 0
- 1
- 1
- 2
- 3
- 4
- 4

**Polynomial Order - Lot Size**

- 0
- 1
- 1
- 1
- 1
- 3
Monocentric city and shrinkage both reduce errors

Column 1 uses a “naive” model of (geometric) average value per acre of all sales by metro.
- Establishes a baseline for other models to improve upon.
Monocentric city and shrinkage both reduce errors

Column 1 uses a “naive” model of (geometric) average value per acre of all sales by metro.

- Establishes a baseline for other models to improve upon.

Column 2: From a monocentric model (21), 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.

- Lowers MSE over naive model substantially by reducing the variance.

Column 3: Applies the empirical Bayes shrinkage technique. Further reduces the variance, while slightly raising bias.

More improvement with smaller samples.

The rest of the table considers minor improvements in distance and lot size polynomials. Column 7 preferred.
Monocentric city and shrinkage both reduce errors

Column 1 uses a “naive” model of (geometric) average value per acre of all sales by metro.
- Establishes a baseline for other models to improve upon.

Column 2: From a monocentric model (21), 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.
- Lowers MSE over naive model substantially by reducing the variance.

Column 3: Applies the empirical Bayes shrinkage technique.
- Further reduces the variance, while slightly raising bias.
- More improvement with smaller samples.

The rest of the table considers minor improvements in distance and lot size polynomials. Column 7 preferred.
We calculate the predicted land value $\hat{r}_{ljt}$ at the tract centroid.

- based on expected characteristics $X$ (planned use & lot size) of the tract, (conditional on city, distance from center and coast, and observed transactions)
- multiply by the area of each tract $A_{jl}$, excl. non-urban block groups
- total value in city $j$ is $R_{jt} = \sum_l A_{jl} \hat{r}_{ljt}$; average 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. Estimated “meta-city” allows us to impute values for metros without observations.
Land Value Gradient Estimates for the Houston

Estimated Land Value Surface with Census Tract Centroids
Patterns in the Data

We report three key features of the land estimates:

1. Central land values (1/2 mile from exact center)
2. Ratio of central value to 10 miles away.
3. Average land value

Effect of shrinkage shown graphically:

- Grey dots represent unshrunken estimates; dark dots, the shrunken.
- Vertical distances reflect shrinkage effect.
  - Larger cities, with more observations, experience less shrinkage.

Empirical results support monocentric city with convex rent gradients.

- Gradients steepen towards the center
  - firms and households sort according to how their bid varies with distance.
  - agents substitute away from using land as it rises in price.
### Selected Metropolitan Land Value Indices, 2005-2010

**Land Values - $000s/Acre**

<table>
<thead>
<tr>
<th>Rank</th>
<th>Name of Metro Area (PMSA)</th>
<th>Area Sq Mi</th>
<th>No. Sales</th>
<th>Naive Avg</th>
<th>Central 1/2 Mi</th>
<th>Average of All .5/10</th>
<th>Total $Bil</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>New York, NY</td>
<td>749</td>
<td>1,603</td>
<td>26,139</td>
<td>123,335</td>
<td>5,264</td>
<td>22.3</td>
</tr>
<tr>
<td>2</td>
<td>Jersey City, NJ</td>
<td>47</td>
<td>43</td>
<td>7,667</td>
<td>9,554</td>
<td>3,305</td>
<td>8.8</td>
</tr>
<tr>
<td>3</td>
<td>Honolulu, HI</td>
<td>198</td>
<td>56</td>
<td>4,357</td>
<td>16,256</td>
<td>3,290</td>
<td>7.0</td>
</tr>
<tr>
<td>4</td>
<td>San Francisco, CA</td>
<td>300</td>
<td>152</td>
<td>8,722</td>
<td>25,446</td>
<td>3,239</td>
<td>9.3</td>
</tr>
<tr>
<td>5</td>
<td>Los Angeles-Long Beach, CA</td>
<td>1,359</td>
<td>1,760</td>
<td>3,709</td>
<td>16,801</td>
<td>2,675</td>
<td>5.5</td>
</tr>
<tr>
<td>16</td>
<td>Washington, DC-MD-VA-WV</td>
<td>1,458</td>
<td>1,840</td>
<td>3,548</td>
<td>36,913</td>
<td>1,214</td>
<td>32.6</td>
</tr>
<tr>
<td>22</td>
<td>Las Vegas, NV-AZ</td>
<td>317</td>
<td>2,553</td>
<td>1,193</td>
<td>1,841</td>
<td>849</td>
<td>2.4</td>
</tr>
<tr>
<td>26</td>
<td>Chicago, IL</td>
<td>2,035</td>
<td>3,511</td>
<td>1,455</td>
<td>37,632</td>
<td>663</td>
<td>35.1</td>
</tr>
<tr>
<td>27</td>
<td>Boston, MA-NH</td>
<td>1,295</td>
<td>122</td>
<td>1,243</td>
<td>8,457</td>
<td>600</td>
<td>9.8</td>
</tr>
<tr>
<td>118</td>
<td>Houston, TX</td>
<td>1,341</td>
<td>1,143</td>
<td>423</td>
<td>2,813</td>
<td>272</td>
<td>9.4</td>
</tr>
<tr>
<td>120</td>
<td>Detroit, MI</td>
<td>1,426</td>
<td>679</td>
<td>456</td>
<td>2,321</td>
<td>270</td>
<td>6.6</td>
</tr>
<tr>
<td>323</td>
<td>Jackson, MI</td>
<td>57</td>
<td>8</td>
<td>49</td>
<td>74</td>
<td>38</td>
<td>3.0</td>
</tr>
<tr>
<td>324</td>
<td>Jamestown, NY</td>
<td>46</td>
<td>10</td>
<td>43</td>
<td>63</td>
<td>30</td>
<td>2.1</td>
</tr>
</tbody>
</table>

**Total U.S.**

<table>
<thead>
<tr>
<th>Area Sq Mi</th>
<th>No. Sales</th>
<th>Naive Avg</th>
<th>Central 1/2 Mi</th>
<th>Average of All .5/10</th>
<th>Total $Bil</th>
</tr>
</thead>
<tbody>
<tr>
<td>76,581</td>
<td>68,756</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>25,024.8</td>
</tr>
</tbody>
</table>

**Simple Average U.S.**

- 235      | 212      | 591      | 1,672          | 344                  | 76.8       |

**Simple Std. Dev. across Metros**

- 304      | 592      | 1,660    | 7,472          | 519                  | 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      |
Larger cities tend to have more expensive central land.
Land values in larger cities are much higher centrally than 10 miles away.

- Smallest cities the gradient is typically nearly flat.
- Large cities, the ratio is larger, but highly variable.
Positive, but weaker correlation between city size and average values.
### Estimated Coefficients on Covariates

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Estimates</th>
<th>S.E.</th>
<th>t-stat</th>
<th>p-val</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Lot Size</td>
<td>-0.543</td>
<td>0.0037</td>
<td>-146.134</td>
<td>0.000</td>
</tr>
<tr>
<td>(Log Lot Size Squared)/100</td>
<td>-3.053</td>
<td>0.1592</td>
<td>-19.176</td>
<td>0.000</td>
</tr>
<tr>
<td>(Log Lot Size Cubed)/1000</td>
<td>3.601</td>
<td>0.2498</td>
<td>14.415</td>
<td>0.000</td>
</tr>
<tr>
<td>Log Distance to Coast</td>
<td>-0.052</td>
<td>0.0043</td>
<td>-12.196</td>
<td>0.000</td>
</tr>
</tbody>
</table>

**Planned Use:**

<table>
<thead>
<tr>
<th>Planned Use</th>
<th>Estimates</th>
<th>S.E.</th>
<th>t-stat</th>
<th>p-val</th>
</tr>
</thead>
<tbody>
<tr>
<td>None Listed</td>
<td>-0.182</td>
<td>0.0112</td>
<td>-16.193</td>
<td>0.000</td>
</tr>
<tr>
<td>Commercial</td>
<td>-0.380</td>
<td>0.0599</td>
<td>-6.354</td>
<td>0.000</td>
</tr>
<tr>
<td>Industrial</td>
<td>-0.346</td>
<td>0.0141</td>
<td>-24.578</td>
<td>0.000</td>
</tr>
<tr>
<td>Retail</td>
<td>0.255</td>
<td>0.0134</td>
<td>18.963</td>
<td>0.000</td>
</tr>
<tr>
<td>Single Family</td>
<td>0.003</td>
<td>0.0133</td>
<td>0.202</td>
<td>0.840</td>
</tr>
<tr>
<td>Multifamily</td>
<td>-0.139</td>
<td>0.0198</td>
<td>-7.055</td>
<td>0.000</td>
</tr>
<tr>
<td>Office</td>
<td>0.046</td>
<td>0.0148</td>
<td>3.129</td>
<td>0.002</td>
</tr>
<tr>
<td>Apartment</td>
<td>0.288</td>
<td>0.0196</td>
<td>14.713</td>
<td>0.000</td>
</tr>
<tr>
<td>Hold for Development</td>
<td>-0.073</td>
<td>0.0118</td>
<td>-6.171</td>
<td>0.000</td>
</tr>
<tr>
<td>Hold for Investment</td>
<td>-0.283</td>
<td>0.0195</td>
<td>-14.523</td>
<td>0.000</td>
</tr>
<tr>
<td>Mixed Use</td>
<td>0.250</td>
<td>0.0265</td>
<td>9.438</td>
<td>0.000</td>
</tr>
<tr>
<td>Medical</td>
<td>0.171</td>
<td>0.0355</td>
<td>4.810</td>
<td>0.000</td>
</tr>
<tr>
<td>Parking</td>
<td>0.076</td>
<td>0.0373</td>
<td>2.044</td>
<td>0.041</td>
</tr>
</tbody>
</table>
Comparing Transaction- and Residual-based Estimates

Residual method takes a property’s land value as the difference between its entire value and the estimated value of its structure:

- Structure value typically depreciated construction costs
- Neglects adjustment costs and irreversible investment
- 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.”


- DP is purely owner-occupied residential; ours has renters
- DP is by lot, so we estimate lot acreage by metro using the American Housing Survey

To aggregate, we multiply DP land values by no of units in urban units in the 2000 Census:

- Count rental units as having half the land as an owned.
- Avoids estimating acreages, but misses non-residential land.
Comparison of AES and DP land values

Average value per acre of land by city
- National average of urban land: AES $720K, DP $392K
- Across metros, correlation coefficient = 0.73
- San Francisco: both over $3M
- New York, AES $5.2M, DP: $835K
- Oklahoma City: AES $161K; DP $24K.

Aggregate land values by metro
- Generally lower except in highest cities
- Aggregate more strongly correlated, coefficient = 0.85

Value changes over time are typically smaller within cities over boom & bust
- Coefficient of variation: AES 0.24; DP 0.44
- Same pattern seen in time series for aggregate land values
AES vs. DP: Average Price per Acre

- Estimated Values, correlation = 0.8345
- Best Fit: -12.23 + 1.33 (0.13) * AES Est.

Albouy, Ehrlich, Shin (Illinois & Michigan)

Metropolitan Land Values

January 6, 2018
AES vs. DP: Volatility by Metro

![Graph showing the relationship between Davis and Palumbo within-city price variation and transactions-estimated within-city price variation for various metros. The graph includes data points for cities such as Minneapolis, Detroit, Chicago, Miami, and more. The graph also shows the best fit line with the equation: Best Fit: 28.24 + 0.63 (0.21) * AES Est. The correlation coefficient is 0.445.]
Aggregate Urban Land Values over Time

Strong swing in land values
- Average values peaked in 2006 at $624K per acre.
- By 2009 the average value dropped by 40% to $373K

Ratio of urban land values to gross domestic product declined
- The ratio was 2.1–2.2 in 2005 and 2006
- Declined to 1.2-1.3 by 2009 and 2010.

Residual method using FOF/Financial Accounts data, value
- held by non-financial non-corporate businesses, non-financial corporate businesses, and households and nonprofit organizations (privately held)
- subtract the current-cost net stock of private structures
- In 2006, real estate was valued at $43.3 trillion; structures 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
- signifies urban land is an even more important asset in the U.S. economy.
- Cover different land. Our estimates include public lands for roads, parks, and civic buildings. If this land is worth 40% of the total, only $18.2T is private.
### Urban Land Values in the United States, 2005-2010

<table>
<thead>
<tr>
<th>Year</th>
<th>Average per Acre $K</th>
<th>Total Urban Value $T</th>
<th>Indexed Value 2005=100</th>
<th>GDP (Nominal) $T</th>
<th>Ratio of Land to GDP</th>
<th>Case-Shiller HP Index 2005=100</th>
<th>“FOF” Residual Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>577</td>
<td>28.1</td>
<td>100.0</td>
<td>13.1</td>
<td>2.15</td>
<td>100.0</td>
<td>16.8</td>
</tr>
<tr>
<td>2006</td>
<td>624</td>
<td>30.4</td>
<td>108.1</td>
<td>13.9</td>
<td>2.19</td>
<td>106.8</td>
<td>16.9</td>
</tr>
<tr>
<td>2007</td>
<td>585</td>
<td>28.5</td>
<td>101.3</td>
<td>14.5</td>
<td>1.97</td>
<td>104.8</td>
<td>16.0</td>
</tr>
<tr>
<td>2008</td>
<td>513</td>
<td>25.0</td>
<td>88.9</td>
<td>14.7</td>
<td>1.70</td>
<td>95.5</td>
<td>9.6</td>
</tr>
<tr>
<td>2009</td>
<td>373</td>
<td>18.2</td>
<td>64.6</td>
<td>14.4</td>
<td>1.26</td>
<td>86.5</td>
<td>5.8</td>
</tr>
<tr>
<td>2010</td>
<td>393</td>
<td>19.1</td>
<td>68.0</td>
<td>15.0</td>
<td>1.28</td>
<td>84.2</td>
<td>6.2</td>
</tr>
</tbody>
</table>

- Land values led house prices slightly, and were substantially more volatile
  - Consistent with land leverage hypothesis
- FOF values lower and fall more in percentage. Similar change in absolute $.
Conclusion

Land estimates combines insights from the monocentric city model with empirical Bayesian methods

- to produce novel and plausible estimates of land values,
- Works even in cities with little or no data
- Methods might be applied to estimate other measures, e.g., wages or property prices.

Important conclusions concerning land values and monocentric city

- Consistently negative land-rent gradients across cities
- Enormous differences across cities: central values vary by a factor of 100
- Central values rise and gradients steeper with size of footprint.

- We estimate higher land values than residual approaches - different land!
- Values are higher, less volatile, less likely to be volatile.
- Every approach has its pluses and minuses.

Hopefully a basis for reliable estimates.
Motivation: Standard urban theory suggests that in the presence of a unified land market, the value of land on the urban fringe, say $d$, should equal the land’s value in agricultural use.

- Costs to converting the land, providing infrastructure
- Land-use regulations made reduce conversion possibilities
- Option value may be greatest in growing areas.
Data

Urban Fringe Land Value ($U_j$)
- We cannot identify exactly where the urban fringe is located.
- Define $d_j^*$ as a distance from the location that covers 90% of urbanized area to the city center.
- Define $d_j^{\text{max}}$ as the distance from the farthest tract center to the city center.
- We define the $U_j$ (peripheral urban land value) as the integrated land value over tracts that are located in $[d_j^*, d_j^{\text{max}}]$.

Agricultural Land Value ($L_j$)
- Data available from the USDA economic research service.
- Raw data are at the county level.
- We aggregate these values at the MSA level by taking weighted average of county level values (weight: non-urban land area).
- Distance from access to jobs (city center)
Model for Urban Fringe and Agricultural Land Value

Linear Log-Log model:

\[ \log U_j = \delta + \alpha \log A_j + X_j' \beta + e_i \]

Non-Linear Log-Log model:

\[ \log U_j = \delta + \alpha \log(c + A_j + X_j' \beta) + e_i \]

where

- \( U_j \): Urban fringe land value
- \( A_j \): Agricultural land value
- \( c \): Cost of conversion
- \( X_j \): Other covariates
  - Regulation index
  - Log distance from the city center to \( d_j^* \)
Fig. 3. Equilibrium land rents and prices under uncertainty.
Agricultural and Peripheral Urban Land Values

Non-Agricultural Land Values vs. Agricultural Land Values

Linear Best Fit: $7.52 (0.46) + 0.49 (0.06) \times \text{Agland value}$

Nonlinear Best Fit: Kernel Regression 45-degree line

MSA level

Peripheral Urban Land Value

Nonlinear Best Fit

Kernel Regression

45-degree line
Linear Log-Log Empirical Model

$$\log U_j = \delta + \alpha \log A_j + X_j' \beta + e_i$$

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>7.52</td>
<td>8.5</td>
<td>7.94</td>
</tr>
<tr>
<td></td>
<td>(0.462)</td>
<td>(0.592)</td>
<td>(0.599)</td>
</tr>
<tr>
<td>$\log A_i$</td>
<td>0.491</td>
<td>0.376</td>
<td>0.453</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.070)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>Regulation</td>
<td>0.222</td>
<td>1.84</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.063)</td>
<td></td>
</tr>
<tr>
<td>Pop. Growth</td>
<td></td>
<td>0.203</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.046)</td>
<td></td>
</tr>
<tr>
<td>$d_j^*$</td>
<td></td>
<td>-0.017</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>318</td>
<td>281</td>
<td>281</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.213</td>
<td>0.253</td>
<td><strong>0.317</strong></td>
</tr>
</tbody>
</table>
Non-Linear Log-Log Empirical Model

\[ \delta + \alpha \log(c + A_j + X'_j\beta) + e_i \]

<table>
<thead>
<tr>
<th>Nonlinear models</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conversion cost</td>
<td>6860</td>
<td>9529</td>
<td>8339</td>
</tr>
<tr>
<td></td>
<td>(1093)</td>
<td>(2035)</td>
<td>(1830)</td>
</tr>
<tr>
<td>log(A_i)</td>
<td>1.24</td>
<td>1.22</td>
<td>1.24</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Regulation</td>
<td>2306</td>
<td>1024</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(864)</td>
<td>(738)</td>
<td></td>
</tr>
<tr>
<td>Pop. Growth</td>
<td>1540</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(573)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(d_j^*)</td>
<td></td>
<td>-144.9</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(70.7)</td>
<td></td>
</tr>
<tr>
<td>(N)</td>
<td>318</td>
<td>281</td>
<td>281</td>
</tr>
<tr>
<td>BIC</td>
<td>685.4</td>
<td>611.4</td>
<td>590.6</td>
</tr>
</tbody>
</table>
Urban fringe land value and agricultural land value are positively correlated.

Nonlinear model is preferred by the Bayesian Information Criteria (BIC).

Intercept in the nonlinear specification is not significant.

For the typical city, an acre of land at the urban fringe appears to derive roughly 60% of its value from improvements

Implied const of conversion for city $j$:

$$\hat{c}_j = \hat{c} + X_j'\hat{\beta}$$

Value from improvements = $\hat{c}_j/(\hat{c}_j + A_j)$ and its average is about 60%.

This is consistent with Mills’ (1998) “guess” that land at the urban fringe derives roughly 50% of its value from improvements.

The slope coefficient $\beta$ in the non-linear model is about 1.24, which is slightly larger than one.
Consider a simpler version of our model of log land price \( i \) in city \( j \),

\[
\log r_{ij} = \alpha_j + \delta_j d_{ij} + e_{ij}
\]

taking out \( t \), covariates, and higher order polynomials for simplicity, where

- \( \alpha_j \): Central land value in the city \( j \)
- \( \delta_j \): Gradient of the land value in the city \( j \)
- \( d_{ij} \): distance of lot \( i \) from the city center

Now allow for parameter \( \delta \) to depend on the angle from the center \( \theta \)

\[
\log r_i = \alpha + \delta_j(\theta_i) d_i + e_i
\]

For instance, is there an “East Side Story” (Heblich et al. 2016) in U.S.?
Is directional information important?

The land value gradient varies over the angle:

\[ \log r_i = \alpha + \delta_j(\theta_i) d_i + e_i \]

Kernel estimation of \( \delta(\theta) \) for Houston

Blue line: Estimated linear land value gradient
Is directional information relevant for us?

Kernel estimation of $\delta(\theta)$ for 10 largest cities

Empirical challenge: For cities with a smaller number of transactions, semi-parametric estimation can be costly.

Solution: Shrinkage estimation.
Shrinkage estimation with a direction gradient

A model of a directional gradient,

$$\log r_{ij} = \alpha_j + \delta_j(\theta_{ij})d_{ij} + e_{ij}$$

Consider a prior for $\delta_j(\theta_k)$ on $[-\pi, \pi]$.

$$\delta_j(\theta_k) = (1 - \rho_{\delta,j})\bar{\delta}_j + \rho_{\delta,j}\delta_j(\theta_{k'}) + v_k, \quad v_k \sim \mathcal{N}(0, \sigma_{\delta,j}^2||\theta_k - \theta_{k'}||)$$

$$\bar{\delta}_j \sim \mathcal{N}(m_0, V_0) \text{ and } \rho_{\delta,j} \sim \mathcal{N}(m_1, V_1).$$

Implication

- When $\sigma_{\delta,j}^2 = 0$ and $\rho_{\delta,j} = 0$, $\delta_j(\theta_k) = \bar{\delta}_j \sim \mathcal{N}(m_0, V_0)$. (AES, 2017)

- When $\sigma_{\delta,j}^2 \neq 0$ and $\rho_{\delta,j} \neq 0$, a gradient can differ by angle.
  - **Shrinkage within city**: Adjacent gradients $\delta_j(\theta_k)$ and $\delta_j(\theta_{k'})$ are close to each other. $\rho_{\delta,j}$ and $\sigma_{\delta,j}^2$ capture this similarity of adjacent gradients.
  - **Shrinkage across city**: Directional gradients are centered around $\bar{\delta}_j$. As $V_0 \to 0$, the center of gradient asymptotes to the national-level gradient.

- $m_0 = a + bA_j$ where $A_j$ is a city characteristic: Shrinkage target differs by the city characteristic.
A model of log land price $i$ in city $j$ at time $t$,

$$\log r_{ij} = \alpha_{jt}(\theta_i) + \delta_j(\theta_i) d_{ij} + \beta' X_{ijt} + e_{ij}$$  \hspace{1cm} (2)$$

where

- $\alpha_{jt}$: Central land value in the city $j$ at time $t$
- $\delta_j$: Gradient of the land value in the city $j$
- $d_{ij}$: distance of lot $i$ from the city center
- $X_{ijt}$: other covariates

We are currently developing an empirical model and associated estimation technique that the city-level spatial function $(\alpha_{jt}(\theta) + \delta_j(\theta)d)$ is shrunken toward a national-level spatial function $(\alpha^*_t(\theta) + \delta^*_d)$

- Amount of shrinkage for each city depends on the number of observations available for that city
- Shrinkage target can differ by city characteristics
- More flexible gradient (i.e., does not have to be linear in $d$)