METROPOLITAN LAND VALUES

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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)
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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

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Key at unlocking what drives housing prices

- How much does geograpahy and land-use restrictions contribute?
- What regulations hurt the most.
- Do we see quality of life benefits from land-use benefits?

Introduction: What We Do and Do Differently

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.

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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!

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Provide a measure of aggregate land values across all cities.

- Changes over time
- Consistently positive, unlike flow of funds...

Related Literature on Land Values

Nichols, Oliner, Mulhall (2013) produce time series for 20 cities

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Problem with negative values

1. DH: Negative value for all residential land in 1940
2. DP: Zero or negative value in some cities.
3. Larson (2015) FOF approach implied land values in the corporate business sector worth negative $178 billion in 2009.

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

Overview of Talk

Preview of Conclusions

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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.

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Measure varies considerably from “residual” measures

- For most cities our values are higher
- Less volatile over time
- Never produce negative values

Data – Land Sales

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.

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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.

Data – Defining Urban Metropolitan Land

"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.

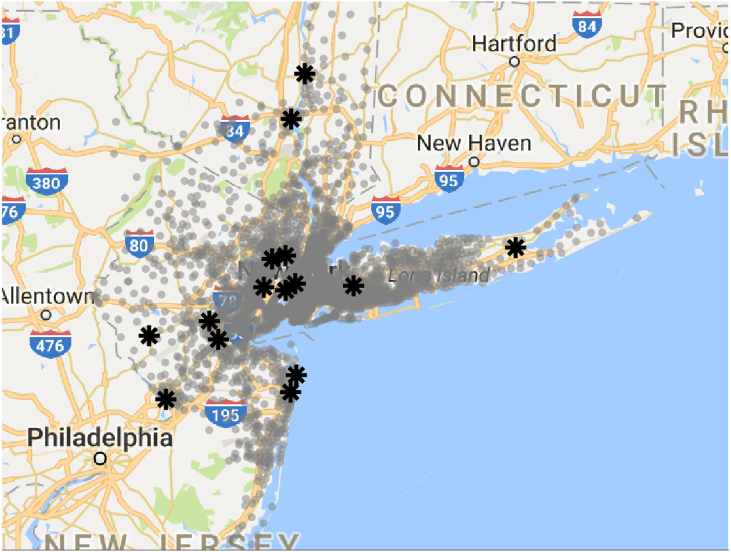
- Block group has a min. density of 1,000 per square mile
- Contiguous with other urban block groups.

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

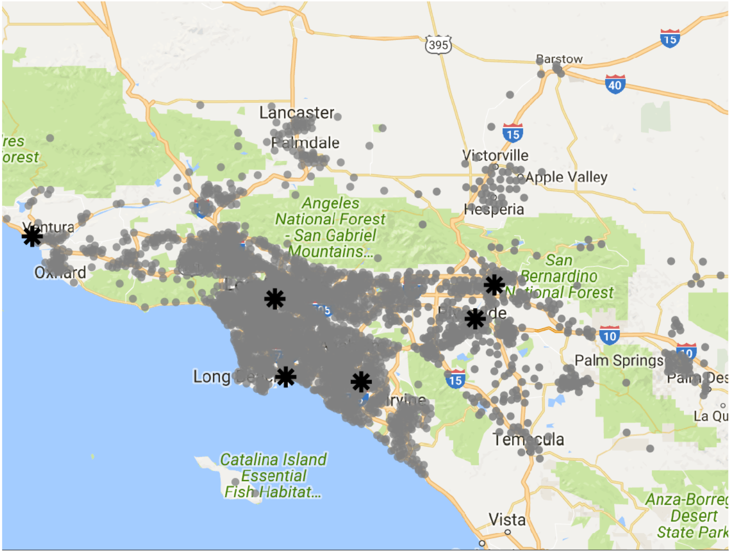
New York Northern New Jersey, Long Island

Gray dots: Land sales
Black stars: City centers



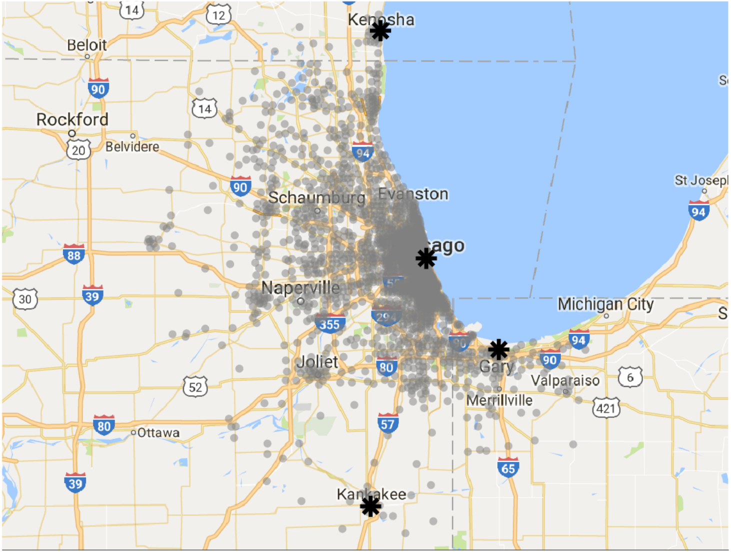
Los Angeles-Riverside-Orange County

Gray dots: Land sales
Black stars: City centers



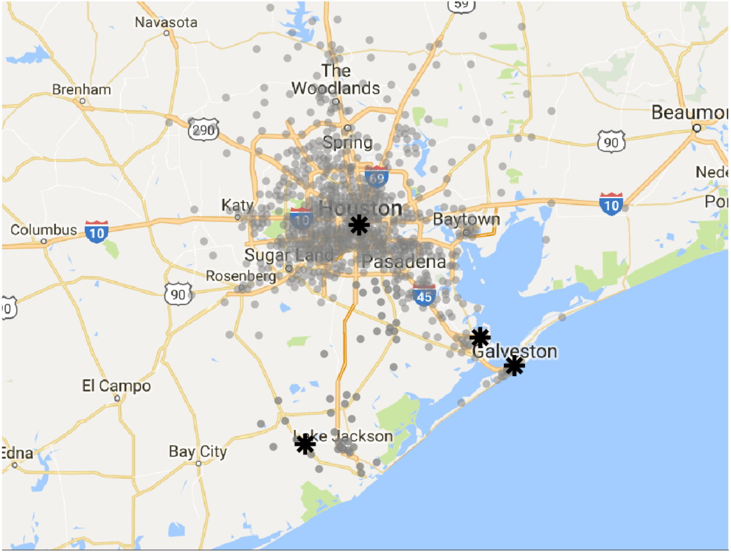
Chicago-Gary-Kenosha

Gray dots: Land sales
Black stars: City centers



Houston-Galveston-Brazoria

Gray dots: Land sales
Black stars: City centers



Econometric Methods – Two obstacles

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**)

Model of Land Values over Space and Time

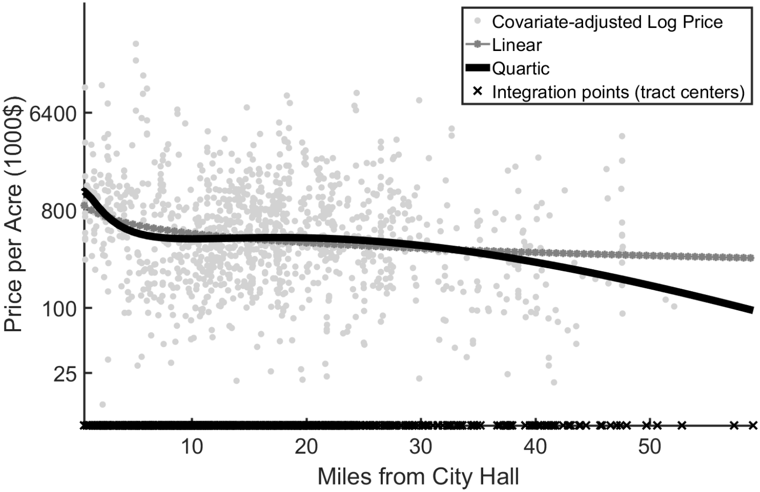
For a lot i in city j at time t, the land value r_{ijt}:

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

- 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:
- 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 $D = \ln(1 + \text{mileage})$



Shrinkage Estimation via Hierarchical Modeling

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

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

- It "shrinks" metro-level estimates (α_{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 (α_{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}:

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We begin by decomposing the central value α_{jt} into two components,

$$\alpha_{jt} = \alpha_j + \alpha_{jt}^{\star}$$

where $\alpha_{j2005}^{\star}$ is normalized to zero.

Time-varying component follows the prior $\alpha_{jt}^{\star} \sim N(\tau_t, \sigma_t^2)$.

- Time-varying components of central values vary across cities and time
- City-level trend fluctuates around the national-level trend, τ_t.
- Heterogeneity in MSA-level departures changes over time through σ_t^2.

Shrinkage Estimation – Time-invariant component

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

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

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

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

where

$$\begin{bmatrix} e_{\alpha,j} \\ \mathbf{e}_{\delta,\mathbf{j}} \end{bmatrix} \sim \text{ i.i.d. } N\left(\begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix}, \begin{bmatrix} \Sigma_{\alpha\alpha} & \boldsymbol{\Sigma_{\alpha\delta}} \\ \boldsymbol{\Sigma_{\delta\alpha}} & \boldsymbol{\Sigma_{\delta\delta}} \end{bmatrix} \right)$$

Shrinkage Estimation – The Meta-city!

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

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

- 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 $\mathbf{e}_{\delta,\mathbf{j}}$.

Shrinkage Estimation – Implication

If 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 metacity (prior mean) and conventional metro-level (fixed effect) estimates, $[\widehat{\alpha}_j, \widehat{\boldsymbol{\delta}}_j]'$:

$$\begin{bmatrix} \widetilde{\alpha}_j \\ \widetilde{\boldsymbol{\delta}}_j \end{bmatrix} = \mathbf{W_j} \underbrace{\begin{bmatrix} a_0 & a_1 \\ \mathbf{d_0} & \mathbf{d_1} \end{bmatrix} \begin{bmatrix} 1 \\ \ln A_j \end{bmatrix}}_{\text{Metacity (Prior mean)}} + (\mathbf{I} - \mathbf{W_j}) \underbrace{\begin{bmatrix} \widehat{\alpha}_j \\ \widehat{\boldsymbol{\delta}}_j \end{bmatrix}}_{\text{Data}} \tag{1}$$

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 (i.e., more weight on data)
- rises with the uncertainty in the prior $(\boldsymbol{\Sigma}_{\alpha\alpha}, \boldsymbol{\Sigma}_{\delta\alpha}, \boldsymbol{\Sigma}_{\delta\delta})$ and the idiosyncratic error term, σ_e^2 (i.e., less weight on data)

We estimate metacity parameters $(a_0, a_1, \mathbf{d}_0, \mathbf{d}_1)$ and their variance $(\boldsymbol{\Sigma}_{\alpha\alpha}, \boldsymbol{\Sigma}_{\delta\alpha}, \boldsymbol{\Sigma}_{\delta\delta})$ so that the estimated Metacity is the national average.

Estimating the Empirical Full Model

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

$$\alpha_{jt} = \alpha_j + \alpha_{jt}^\star, \quad \alpha_{jt}^\star \sim N(\tau_t, \sigma_t^2)$$

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We estimate fixed parameters $(\beta, a_0, a_1, \mathbf{d}_0, \mathbf{d}_1, \tau_{2006}, ..., \tau_{2010})$ and variance parameters $(\sigma^2, \Sigma_{\alpha\alpha}, \boldsymbol{\Sigma_{\alpha\delta}}, \boldsymbol{\Sigma_{\delta\delta}}, \sigma_{2006}^2, ..., \sigma_{2010}^2)$. Adopt an empirical

Bayes-type approach: parameters are found by maximizing the marginal likelihood with a flat (improper) prior.

Cross-Validation: Practical Value of Shrinkage

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.

Cross-Validation Results Support Methodology

	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

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.

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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.

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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.

Integrating Land Values Over the Urban Area

We calculate the predicted land value $\hat{r}_{ljt}$ at the tract centroid.

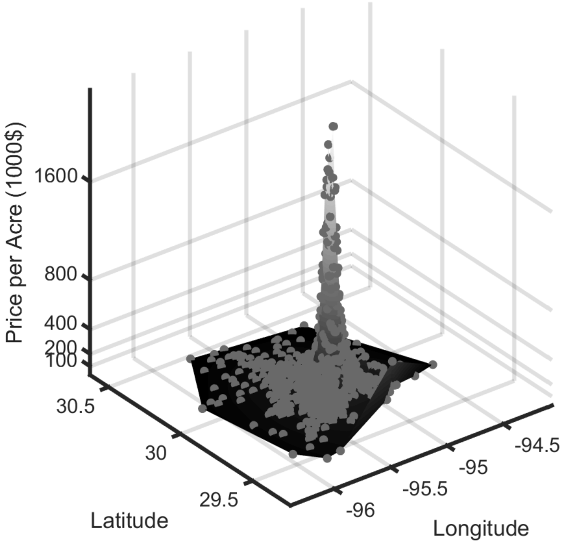
- based on expected characteristics X (planned use & lot size) of the tract, (conditional on city, distance from center and coast, and observed transactions)
- multiply by the area of each tract A_{jl}, excl. non-urban block groups
- total value in city j is $R_{jt} = \sum_l A_{jl}\hat{r}_{ljt}$; average 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.

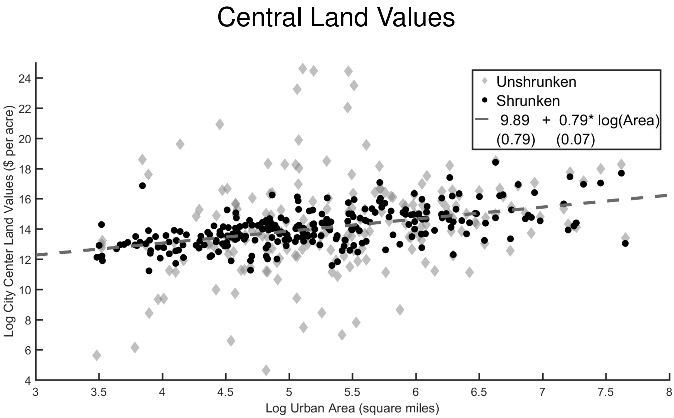
Empirical results support monocentric city with convex rent gradients.

- 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				
Rank	Name of Metro Area (PMSA)	Area Sq Mi	No. Sales	Naive Avg	Central 1/2 Mi	Average of All	Ratio .5/10	Total $Bil
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
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
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
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

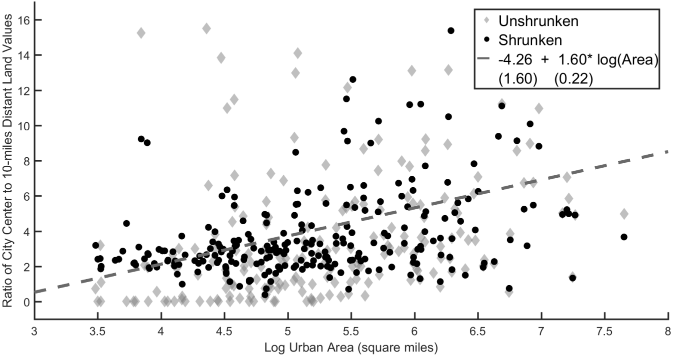
Central Land Values



Larger cities tend to have more expensive central land.

Central to Peripheral Values

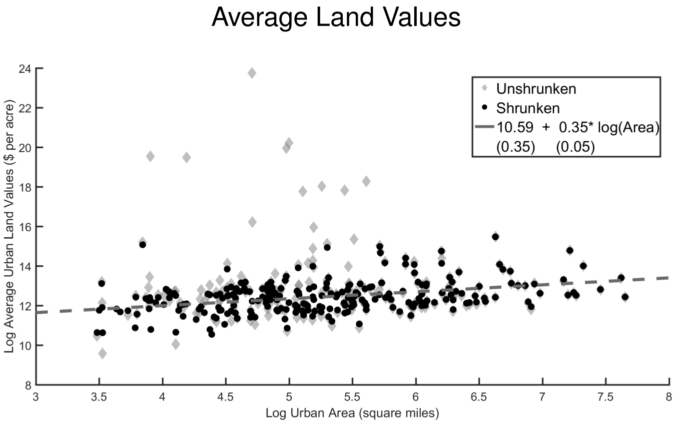
Ratio of Central to 10-mile Distant Land Values



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.

Average Land Values



Ppositive, but weaker correlation between city size and average values.

Estimated Coefficients on Covariates

Covariate	Estimates	S.E.	t-stat	p-val
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

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."

Compare our "AES" values with Davis & Palumbo (2008) "DP" for 46 metros.

- DP is purely owner-occupied residential; ours has renters
- DP is by lot, so we estimate lot acreaage 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.

Coparison 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 Franscisco: both over $3M
- New York, AES $5.2M, DP: $835K
- Oklahoma City: AES $161K; DP $24K.

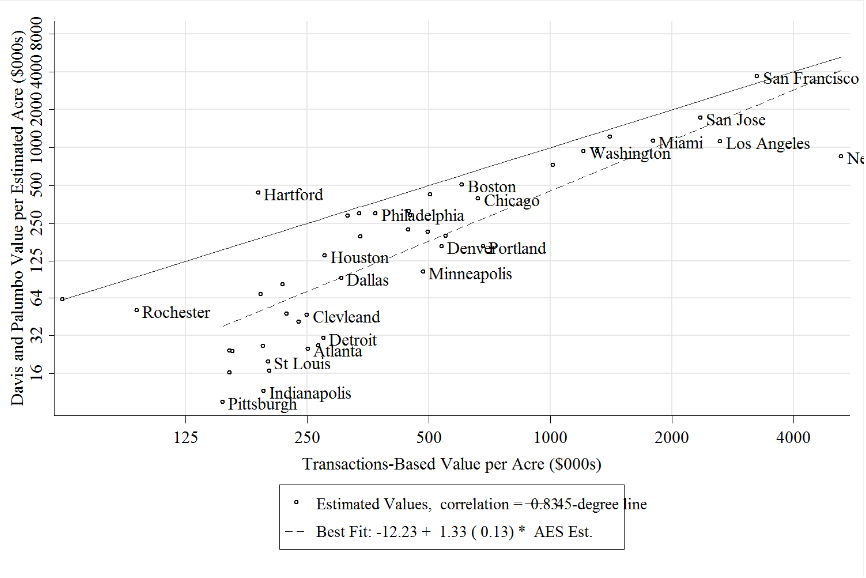
Aggregate land values by metro

- Generally lower except in highest cities
- Aggregate more strongly correlated, coefficient = 0.85

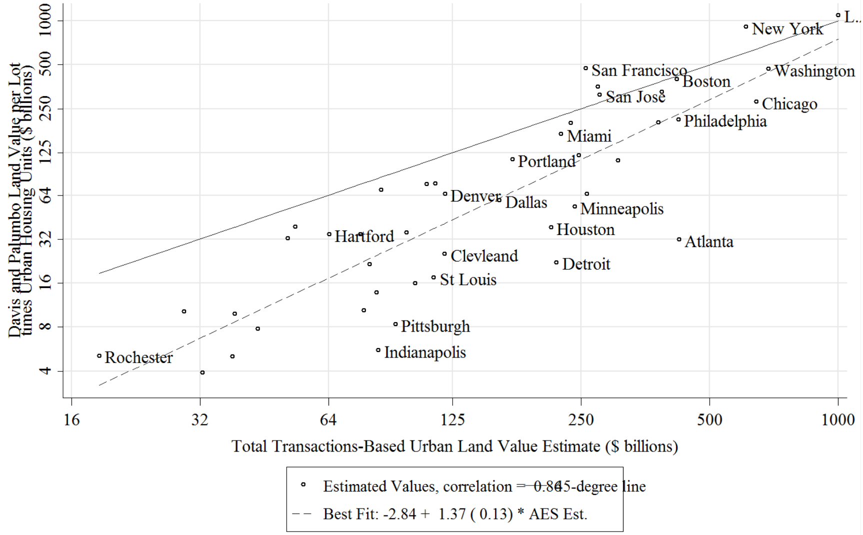
Value changes over time are typically smaller within cities over boom & bust

- Coefficient of variation: AES 0.24; DP 0.44
- Same pattern seen in time series for aggregate land values

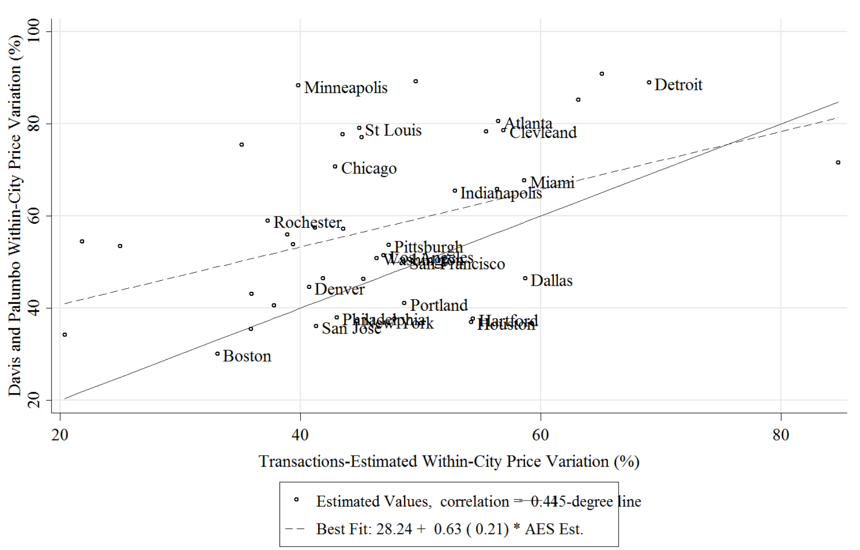
AES vs. DP: Average Price per Acre



AES vs. DP: Aggregate Value By Metro



AES vs. DP: Volatility by Metro



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

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

- 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.

Extension 1: Agricultural and Urban Fringe Values

Motivation: Standard urban theory suggests that in the presence of a unified land market, the value of land on the urban fringe, say $\underline{d}$, 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^{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 $[d_j^*, d_j^{max}]$.

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
  - Population growth (2000–2009)
  - Log distance from the city center to d_j^*

Theory of Urban vs Agricultural Values

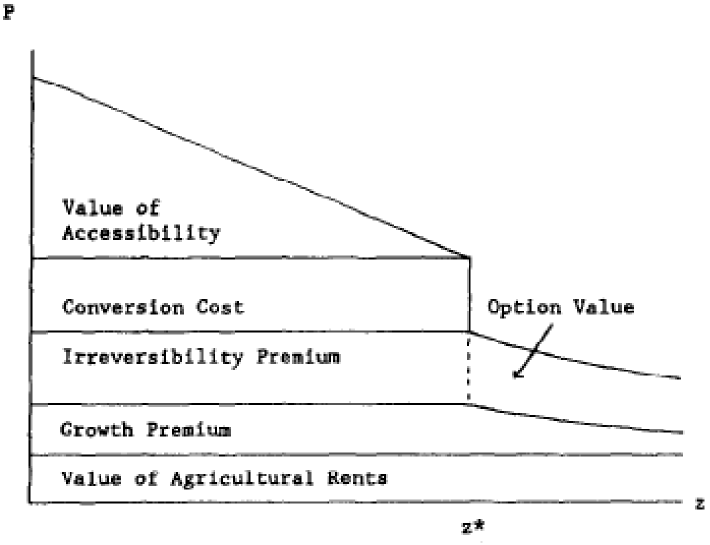
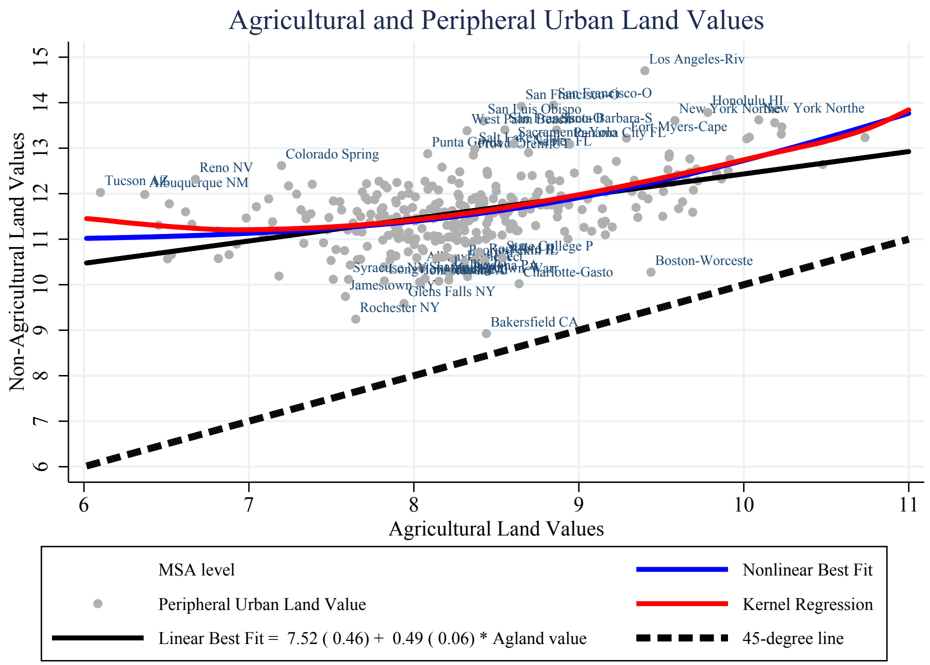


FIG. 3. Equilibrium land rents and prices under uncertainty.


Agricultural and Peripheral Urban Land Values
Non-Agricultural Land Values
Agricultural Land Values
6
7
8
9
10
11
12
13
14
15
Los Angeles-Riv
Honolulu HI
New York Northe
Fort-Myers-Cape
San Luis Obispo
Colorado Spring
Reno NV
Tucson AZ
Albuquerque NM
State College P
Boston-Worceste
Charlotte-Gasto
Jamestown NY
Glens Falls NY
Rochester NY
Bakersfield CA
MSA level
Peripheral Urban Land Value
Linear Best Fit = 7.52 (0.46) + 0.49 (0.06) * Agland value
Nonlinear Best Fit
Kernel Regression
45-degree line

Linear Log-Log Empirical Model

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

	(1)	(2)	(3)
Intercept	7.52	8.5	7.94
	(0.462)	(0.592)	(0.599)
$logA_i$	0.491	0.376	0.453
	(0.055)	(0.070)	(0.072)
Regulation		0.222	1.84
		(0.060)	(0.063)
Pop. Growth			0.203
			(0.046)
d_j^*			-0.017
			(0.007)
N	318	281	281
Adj. R^2	0.213	0.253	**0.317**

Non-Linear Log-Log Empirical Model

$$\delta + \alpha \log(c + A_j + X_j' \beta) + e_i$$

	Nonlinear models		
	(4)	(5)	(6)
Conversion cost	6860	9529	8339
	(1093)	(2035)	(1830)
$logA_i$	1.24	1.22	1.24
	(0.01)	(0.02)	(0.02)
Regulation		2306	1024
		(864)	(738)
Pop. Growth			1540
			(573)
d_j^*			-144.9
			(70.7)
N	318	281	281
BIC	685.4	611.4	**590.6**

Discussion

- 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:

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

  - Value from improvements = $\widehat{c}_j / (\widehat{c}_j + A_j)$ 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 β in the non-linear model is about 1.24, which is slightly larger than one.

Extension 2: Incorporating Angles

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

- α_j: Central land value in the city j
- δ_j: Gradient of the land value in the city j
- d_{ij}: distance of lot i from the city center

Now allow for parameter δ to depend on the angle from the center θ

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

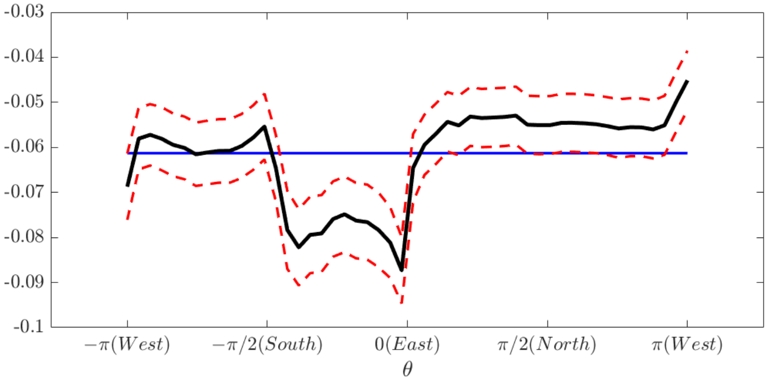
For instance, is there an “East Side Story” (Heblich et al. 2016) in U.S.?

Is directional information important?

The land value gradient varies over the angle:

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

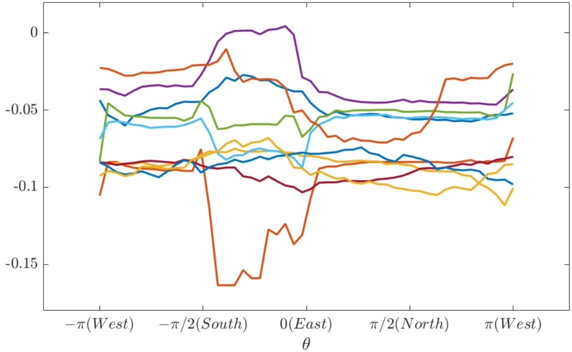
Kernel estimation of $\delta(\theta)$ for Houston



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 $[-\pi, \pi]$.

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

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

Implication

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

A model of log land price i in city j at time t,

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

where

- α_{jt}: Central land value in the city j at time t
- δ_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 ($\alpha_{\star,t}(\theta) + \delta_\star(\theta)d$)

- 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)