

# Implicit Land Taxes and Their Effect on the Real Economy

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# Are land taxes the perfect tax?

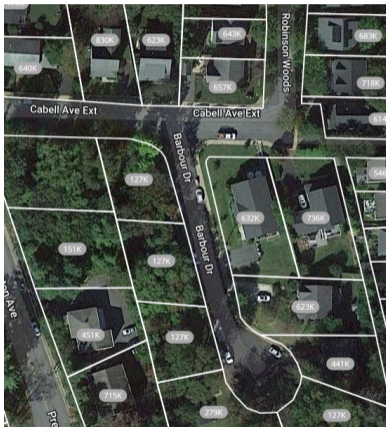
1. Taxing land cannot lead to less land, making it appealing for taxation.
2. Land taxes might
  - increase density (Anderson, 1999; Brueckner and Kim, 2003)
  - decrease negative externalities of pollution and traffic (Banzhaf and Lavery, 2010).
  - remove incentives for speculation (Anderson, 1986, 1993b,a)
  - reduce housing bubbles, increase affordable housing, etc. (Anderson, Alfaro, Allen, Hawley, Hanson, Paredes, Skidmore, and Yang, 2021; Yang and Hawley, 2022)
3. They may also,
  - increase entrepreneurship (Hanson, 2021)
  - increase neighborhood diversity.

This paper provides a national empirical investigation of the effect of land taxes.

# Property tax system discourages structure improvements

- Despite high prices and housing costs, many cities have a lot of vacant land.
  - Atlanta has 13,450 vacant or sparsely built lots.
  - Austin has 17,516
  - New York City 77,371.

# Property taxes on empty lots vs homes

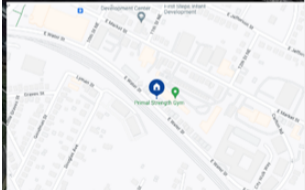


Zestimate \$127,000  
Taxes \$498



Zestimate \$942,400  
Taxes \$5,129

# Disincentive to develop



Zillow

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3 bd | 4 ba | 3,692 sqft

1055 E Water St, Charlottesville, VA 22902

● **Off market** | Zestimate®: **\$1,673,400** | Rent Zestimate®: **\$8,501**

Est. refl payment: \$10,441/mo [Refinance your loan](#)

[Home value](#) [Owner tools](#) [Home details](#) [Neighborhood details](#)

Year	Property taxes	Tax assessment
2022	\$6,768 -47.7%	\$1,409,900 +3.5%
2021	\$12,939	\$1,362,000 +10.4%
2020	--	\$1,233,900 +17.9%
2019	\$1,900	\$1,046,600 +423.3%
2018	\$1,900	\$200,000 +233.3%
2017	--	\$60,000
2016	--	\$60,000

[Show less](#)

# We could have a lot more housing

If all of the vacant land was built on

Austin, TX could add

- over 1 billion sq ft. of housing
- 500,000 apartments (2,000 sq. ft. each)

Altus Group estimates

# Detroit Aims to Spur New Housing, Boost Property Values With Tax Change

*The Wall Street Journal* Feb. 14, 2023, Konrad Putzier.



Detroit has a glut of vacant lots and a lack of development.

PHOTO: JIM WEST/ZUMA PRESS

# Despite the praise, land taxes are not widely adopted

- Proponents of the land tax include
  - Henry George, Alfred Marshall, Paul Samuelson, Milton Friedman, Paul Krugman, and Joseph Stiglitz.
- Land taxes are not widely adopted (though more than typically acknowledged)
  - There are split-rate taxes, for example, in Australia, Denmark, parts of Indonesia, and Pennsylvania (Youngman and Malme, 1994; McCluskey and Franzsen, 2017; Anderson et al., 2021; Hanson, 2021; Yang and Hawley, 2022).

Without explicit land taxes, it is hard to empirically test theoretical predictions.



# Our Approach

The ideal experiment would be to randomly implement land taxes across the US and test their effect on economic variables.

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The ideal experiment would be to randomly implement land taxes across the US and test their effect on economic variables.

## **Our *slightly less ideal* approach**

Exploit random differences between how markets and tax assessors value land.

- Tax assessors combine data on parcel characteristics to produce a tax-assessed value
- Market participants implicitly do the same

When the explicit assessor model values land more than the implicit market model (conditional on the overall property tax rate), there is an ***implicit land tax (ILT)***

# What is the effect of land taxes on economic variables?

1. Develop a measure of **implicit implicit land taxes**
2. Investigate how land taxes affect
  - density
  - neighborhood diversity
  - entrepreneurship
  - wages
3. Develop a model that incorporates our empirical findings and provides insights into the mechanisms of land taxation.

# Data from several sources

1. Sales price, housing characteristics, and property taxes paid (Attom and Zillow)
  - 374 million parcels from 2006 to 2016 (see Gindelsky, Moulton, and Wentland, 2022; Bradley, Huang, and Seegert, 2023).
2. Population density (U.S. Census).
3. Total labor earnings (Quarterly Census of Employment on Wages).
4. Neighborhood diversity (U.S. Census) with entropy measure (White, 1986).
5. Business establishment formation (County Business Patterns).

# Tax assessor model of value for properties

Tax Assessor model for property  $i$  in county  $c$  combines land  $L_i$  (lot sq ft.) and  $J - 1$  building  $S_{j,i}$  characteristics and neighborhood fixed effects  $\lambda_n$

$$A_{i,c} = \beta_{0,c} + \beta_{1,c}L_i + \sum_{j=2}^J \beta_{j,c}S_{j,i} + \lambda_n + \varepsilon_i,$$

building characteristics  $S_{j,i}$  include

- Square footage
- Number of bedrooms
- Number of bathrooms, etc.

# Market model of value for properties

Similarly, households determine their willingness to pay for a property by

1. Gathering data on characteristics of the property.
2. Combining these characteristics into an implicit model to make an offer.

$$M_{i,c} = \delta_{0,c} + \delta_{1,c}L_i + \sum_{j=2}^J \delta_{j,c}S_{j,i} + \phi_n + \nu_i,$$

# Decompose property tax payments into 4 components

Define implicit land taxes as errors off of the level of property tax

1. Level of the property tax.
2. implicit land tax.
3. implicit structures tax.
4. implicit level differences across counties and neighborhoods (entry fee).

# Tax assessor misvaluations lead to implicit land taxes

Start with property tax payments  $T_{i,c}$  add and subtract  $\tau_{e,c}M_i$

$$\begin{aligned}T_{i,c} &= \tau_{s,i,c}A_i \\ &= \tau_{e,c}M_i + \tau_{s,i}A_i - \tau_{e,c}M_i \\ &= \tau_{e,c}M_i + \tau_{s,i}(\beta_{0,c} + \beta_{1,c}L_i + \sum_{j=2}^J \beta_{j,c}S_{j,i} + \lambda_n + \varepsilon_i) \\ &\quad - \tau_{e,c}(\delta_{0,c} + \delta_{1,c}L_i + \sum_{j=2}^J \delta_{j,c}S_{j,i} + \phi_n + \nu_i).\end{aligned}$$

Rearrange terms to pieces on land, structures, and entry fee.



Decompose property tax payments into 4 components:

$$\begin{aligned} E[T_i] &= \tau_{e,c} M_c + \frac{\tau_{s,c} \beta_{1,c} - \tau_{e,c} \delta_{1,c}}{\delta_{1,c}} \delta_{1,c} L_c + \sum_{j=2}^J \frac{\tau_{s,c} \beta_{j,c} - \tau_{e,c} \delta_{j,c}}{\delta_{j,c}} \delta_{j,c} S_{j,c} + \theta \\ &= \tau_{e,c} M_c + ILT_c \delta_1 L_c + \sum_{j=2}^J IST_{j,c} S_{j,c} + \theta, \end{aligned}$$

1. Level of the property tax  $\tau_{e,c} M_c$

Decompose property tax payments into 4 components:

$$\begin{aligned} E[T_i] &= \tau_{e,c} M_c + \frac{\tau_{s,c} \beta_{1,c} - \tau_{e,c} \delta_{1,c}}{\delta_{1,c}} \delta_{1,c} L_c + \sum_{j=2}^J \frac{\tau_{s,c} \beta_{j,c} - \tau_{e,c} \delta_{j,c}}{\delta_{j,c}} \delta_{j,c} S_{j,c} + \theta \\ &= \tau_{e,c} M_c + \text{ILT}_c \delta_1 L_c + \sum_{j=2}^J \text{IST}_{j,c} S_{j,c} + \theta, \end{aligned}$$

2. Implicit land tax  $\text{ILT}_c$

Decompose property tax payments into 4 components:

$$\begin{aligned} E[T_i] &= \tau_{e,c} M_c + \frac{\tau_{s,c} \beta_{1,c} - \tau_{e,c} \delta_{1,c}}{\delta_{1,c}} \delta_{1,c} L_c + \sum_{j=2}^J \frac{\tau_{s,c} \beta_{j,c} - \tau_{e,c} \delta_{j,c}}{\delta_{j,c}} \delta_{j,c} S_{j,c} + \theta \\ &= \tau_{e,c} M_c + ILT_c \delta_1 L_c + \sum_{j=2}^J IST_{j,c} S_{j,c} + \theta, \end{aligned}$$

3. Implicit structures tax  $IST_c$

Decompose property tax payments into 4 components:

$$\begin{aligned} E[T_i] &= \tau_{e,c} M_c + \frac{\tau_{s,c} \beta_{1,c} - \tau_{e,c} \delta_{1,c}}{\delta_{1,c}} \delta_{1,c} L_c + \sum_{j=2}^J \frac{\tau_{s,c} \beta_{j,c} - \tau_{e,c} \delta_{j,c}}{\delta_{j,c}} \delta_{j,c} S_{j,c} + \theta \\ &= \tau_{e,c} M_c + ILT_c \delta_1 L_c + \sum_{j=2}^J IST_{j,c} S_{j,c} + \theta, \end{aligned}$$

4. Implicit level differences  $\theta$

# Tax assessor misvaluations lead to implicit land tax

$$ILT_c \equiv \frac{\tau_{s,c}\beta_{1,c} - \tau_{e,c}\delta_{1,c}}{\delta_{1,c}}$$

1. ILT is the difference in tax assessor and market model.
2. Tax if assessor over-values land relative to the market.
3. Subsidy if assessor under-values relative to the market.
4. Plausibly exogenous.

# Examples

Tax-assessor model is

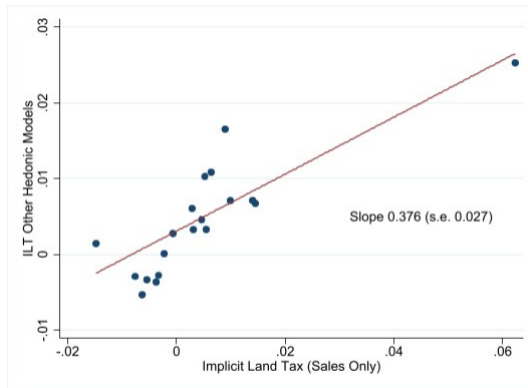
1. the market model, e.g.,  $A_i = M_i$ ,  $\beta_{1,c} = \delta_{1,c}$ , and  $\tau_{s,c} = \tau_{e,c}$ .

$$\text{ILT}_c \equiv \frac{\tau_{s,c}\beta_{1,c} - \tau_{e,c}\delta_{1,c}}{\delta_{1,c}} = 0$$

2. correct on average but not in each component, e.g.,  $\tau_{s,c} = \tau_{e,c}$  but  $\beta_{1,c} \neq \delta_{1,c}$ .

$$\text{ILT}_c \equiv \tau_{s,c} \left( \frac{\beta_{1,c}}{\delta_{1,c}} - 1 \right)$$

# Robust to other hedonic models



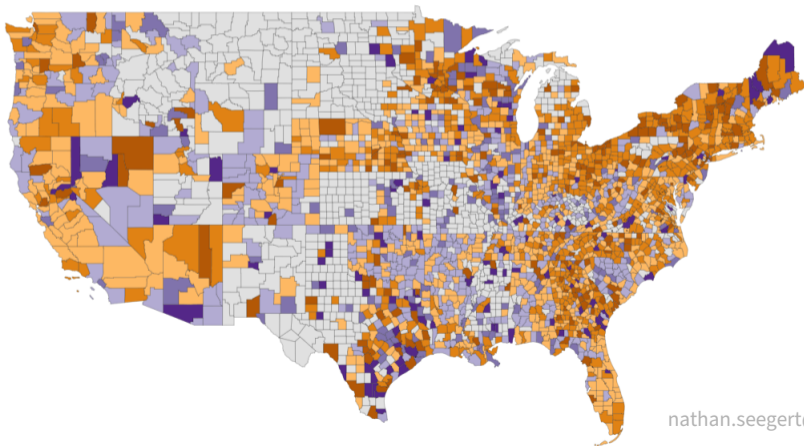
Thank you to John Anderson for asking us to investigate this.

# Lots of variation in implicit land taxes





- Large land tax 2% to 5%
- Medium land tax 0.5% to 2%
- Small land tax 0% to 0.5%
- Small land subsidy 0% to 0.5%
- Medium land subsidy 0.5% to 2%
- Large land subsidy 2% to 5%
- No data



# Land taxes are not correlated with county characteristics

	ILT	N
Correlation Coefficients	(1)	(2)
Land price	-0.15	1867
White share	-0.03	2066
Property Value	0.02	1965
Density	0.08	2046
Population-weighted density	0.01	2047
Racial diversity	-0.01	2047
Labor income	0.05	2046
Establishments	0.05	2060
Land Use Regulations	0.08	912
Land Supply Elasticity	-0.02	712

This table reports correlation coefficients between the ILT (computed using the Sales-Only method) and county characteristics. Variables are year-2000 log-levels.

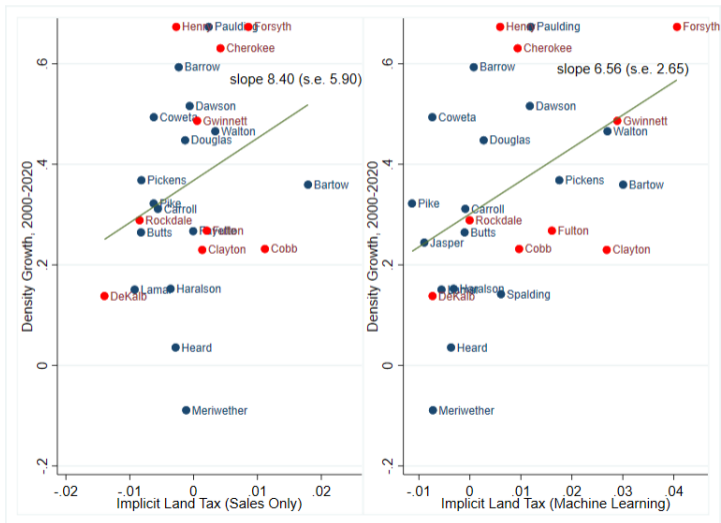
# Counties with the largest land tax and subsidy

	County	CBSA	State	implicit Land Tax	Effective Property Tax
				(1)	(2)
Largest subsidy	Clinton	St. Louis, MO-IL	Illinois	-0.039	0.007
	St.		New York	-0.039	0.003
	Marshall	Memphis, TN-MS-AR	Mississippi	-0.039	0.010
	Polk		Texas	-0.039	0.000
	Wharton		Texas	-0.039	0.019
	Carson	Amarillo, TX	Texas	-0.038	0.016
	Milam		Texas	-0.038	0.003
	Milwaukee	Milwaukee, WI	Wisconsin	-0.038	0.004
	Coryell	Killeen, TX	Texas	-0.038	0.000
	Hill		Texas	-0.038	0.004
Largest tax	Mineral		Colorado	0.039	0.048
	Calhoun	Battle Creek, MI	Michigan	0.040	0.018
	Brantley	Brunswick, GA	Georgia	0.040	0.008
	Livingston	Baton Rouge, LA	Louisiana	0.040	0.006
	Washington	St. George, UT	Utah	0.041	0.000
	Otter		Minnesota	0.042	0.004
	Raleigh		West Virginia	0.042	0.003
	Nicholas		West Virginia	0.044	0.000
	Wright	Twin cities, MN-WI	Minnesota	0.044	0.001

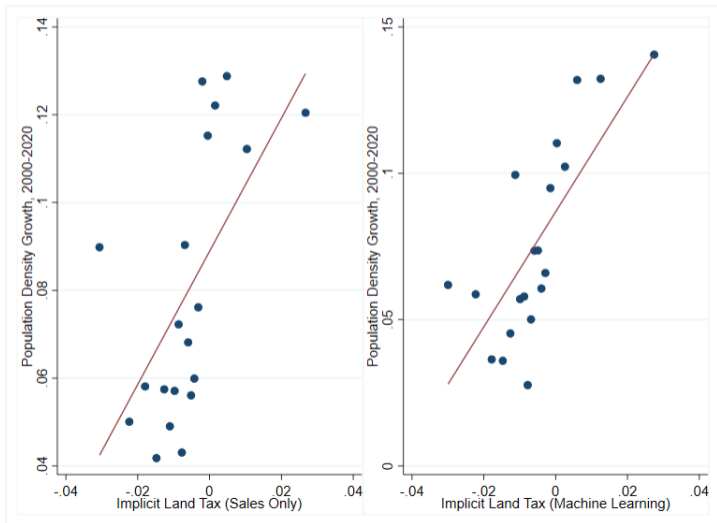
# Lots of variation in land taxes within MSA

CBSA	No. of counties with ILT estimates	Mean ILT	St Dev of ILT
	(1)	(2)	(3)
Atlanta-Sandy Springs-Marietta, GA	25	-0.001	0.007
Washington-Arlington-Alexandria, DC-VA-MD-WV	21	-0.001	0.008
Richmond, VA	18	-0.001	0.009
Virginia Beach-Norfolk-Newport News, VA-NC	14	-0.003	0.010
Chicago-Joliet-Naperville, IL-IN-WI	13	-0.017	0.009
Cincinnati-Middletown, OH-KY-IN	13	-0.006	0.008
St. Louis, MO-IL	12	-0.015	0.013
Nashville-Davidson-Murfreesboro-Franklin, TN	11	-0.002	0.005
New York-Northern New Jersey-Long Island, NY-NJ-PA	11	0.004	0.017
Louisville/Jefferson County, KY-IN	11	-0.008	0.006
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	10	-0.007	0.008
Denver-Aurora-Broomfield, CO	10	-0.001	0.011
Indianapolis-Carmel, IN	10	-0.002	0.012
Omaha-Council Bluffs, NE-IA	8	0.003	0.017
Columbus, OH	8	0.003	0.010
Kansas City, MO-KS	8	-0.010	0.012

# ILT are correlated with density growth within MSA



# ILT are correlated with density growth across US



# Baseline specification

$$\% \Delta Y_c = \alpha_s + \gamma \text{ILT}_c + X_c \Gamma + e_c.$$

1.  $\% \Delta Y_c$  includes density, wage earnings, diversity, new businesses.
2.  $\gamma$  coefficient of interest.
3.  $\alpha_s$  state fixed effects.
4.  $X_c \Gamma$  year-2000 controls.

# Potential confounding factors

- X Level differences between tax assessor and market (e.g., tax assessors shift assessments down).
- X Higher land supply areas have lower property values and lower density.
- X Higher land value areas also have higher density.
- O Determinants of the difference between tax assessor and market correlated with changes in economic outcomes—if growing counties are more likely to outsource their tax assessments to vendors and these vendors systematically overvalue land relative to the market.



# Land taxes have a large and positive effect on density

A 1% land tax leads to 1.9% increase in density over two decades

Panel A: Sales Only		Dependent Variable: Population Density Growth 2000-20							
Sample:	Full Sample		Stable ILT estimates pre and post		Precise ILT estimates		Both restrictions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Implicit Land Tax	1.478*** (0.622)	1.919*** (0.396)	2.849*** (0.927)	3.589*** (0.956)	2.682*** (0.834)	3.081*** (0.725)	4.646*** (1.346)	6.618*** (1.422)	
State fixed effects		Y		Y		Y		Y	
Observations	2045	2045	1034	1034	1441	1441	863	863	
R-Square	0.009	0.224	0.016	0.255	0.017	0.254	0.031	0.315	

This table reports coefficients from county-level regressions of growth in population density on the *implicit land tax* given in equation (30). We report bootstrapped standard errors, clustered at the state level, in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

# Land taxes have a large and positive effect on density

The effects are stronger in counties where ILT is more persistent

Panel A: Sales Only		Dependent Variable: Population Density Growth 2000-20							
Sample:	Full Sample		Similar ILT estimates pre and post		Precise ILT estimates		Both restrictions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Implicit Land Tax	1.478*** (0.622)	1.919*** (0.396)	2.849*** (0.927)	3.589*** (0.956)	2.682*** (0.834)	3.081*** (0.725)	4.646*** (1.346)	6.618*** (1.422)	
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# Land taxes have a large and positive effect on density

The effects are stronger in counties where ILT is more precisely estimated

Panel A: Sales Only		Dependent Variable: Population Density Growth 2000-20							
Sample:	Full Sample		Similar ILT estimates pre and post		Precise ILT estimates		Both restrictions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Implicit Land Tax	1.478*** (0.622)	1.919*** (0.396)	2.849*** (0.927)	3.589*** (0.956)	2.682*** (0.834)	3.081*** (0.725)	4.646*** (1.346)	6.618*** (1.422)	
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# Land taxes have a large and positive effect on density

The effects are stronger in counties where ILT is more persistent and precisely estimated

Panel A: Sales Only		Dependent Variable: Population Density Growth 2000-20							
Sample:	Full Sample		Similar ILT estimates pre and post		Precise ILT estimates		Both restrictions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Implicit Land Tax	1.478*** (0.622)	1.919*** (0.396)	2.849*** (0.927)	3.589*** (0.956)	2.682*** (0.834)	3.081*** (0.725)	4.646*** (1.346)	6.618*** (1.422)	
State fixed effects		Y		Y		Y		Y	
Observations	2045	2045	1034	1034	1441	1441	863	863	
R-Square	0.009	0.224	0.016	0.255	0.017	0.254	0.031	0.315	

This table reports coefficients from county-level regressions of growth in population density on the *implicit land tax* given in equation (30). We report bootstrapped standard errors, clustered at the state level, in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

# Land taxes have a large and positive effect on density

The effects are similar using the machine learning sample

Panel B: Machine Learning		Dependent Variable: Population Density Growth 2000-2020							
		Sample: Full Sample		Similar ILT estimates pre and post		Precise ILT estimates		Both restrictions	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implicit Land Tax		1.679** (0.766)	1.890*** (0.713)	2.334*** (0.923)	2.484*** (1.021)	2.109* (1.084)	2.557*** (0.824)	3.128*** (1.199)	3.620*** (1.266)
State fixed effects			Y		Y		Y		Y
Observations		2176	2176	1007	1007	1915	1915	937	937
R-Square		0.015	0.229	0.021	0.254	0.019	0.241	0.029	0.280

This table reports coefficients from county-level regressions of growth in population density on the *implicit land tax* given in equation (30). We report bootstrapped standard errors, clustered at the state level, in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

# Estimates are robust to different specifications and controls

## Estimates are robust to CBSA fixed effects

	Dependent variable: Density Growth, 2000-2020							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implicit Land Tax	1.977*** (0.699)	1.551*** (0.365)	1.202*** (0.357)	1.672*** (0.585)	1.455** (0.679)	1.911*** (0.393)	1.764*** (0.421)	1.132*** (0.397)
Effective Property Tax		-5.131*** (1.849)						
CBSA fixed effects	Y							
State fixed effects		Y	Y	Y	Y	Y	Y	Y
Year-2000 controls			Y					Y
Land Use Regulation control				Y				
Land Supply Elasticity control					Y			
Tax Assessor Characteristics						Y		
Hedonic model with Zip FE							Y	Y
Observations	1388	2021	2036	907	709	2045	2048	2039
R-Square	0.712	0.237	0.392	0.310	0.276	0.225	0.225	0.400

This table reports coefficients from county-level regressions of growth in population density on the *implicit land tax*.

Standard errors clustered at the state level are reported in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

# Estimates are robust to different specifications and controls

Estimates are robust to controls for effective property tax and year 2000 characteristics

	Dependent variable: Density Growth, 2000-2020							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implicit Land Tax	1.977*** (0.699)	1.551*** (0.365)	1.202*** (0.357)	1.672*** (0.585)	1.455** (0.679)	1.911*** (0.393)	1.764*** (0.421)	1.132*** (0.397)
Effective Property Tax		-5.131*** (1.849)						
CBSA fixed effects	Y							
State fixed effects		Y	Y	Y	Y	Y	Y	Y
Year-2000 controls			Y					Y
Land Use Regulation control				Y				
Land Supply Elasticity control					Y			
Tax Assessor Characteristics						Y		
Hedonic model with Zip FE							Y	Y
Observations	1388	2021	2036	907	709	2045	2048	2039
R-Square	0.712	0.237	0.392	0.310	0.276	0.225	0.225	0.400

This table reports coefficients from county-level regressions of growth in population density on the *implicit land tax*.

Standard errors clustered at the state level are reported in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

# Estimates are robust to different specifications and controls

## Estimates are robust to land use and supply controls

	Dependent variable: Density Growth, 2000-2020							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implicit Land Tax	1.977*** (0.699)	1.551*** (0.365)	1.202*** (0.357)	1.672*** (0.585)	1.455** (0.679)	1.911*** (0.393)	1.764*** (0.421)	1.132*** (0.397)
Effective Property Tax		-5.131*** (1.849)						
CBSA fixed effects	Y							
State fixed effects		Y	Y	Y	Y	Y	Y	Y
Year-2000 controls			Y					Y
Land Use Regulation control				Y				
Land Supply Elasticity control					Y			
Tax Assessor Characteristics						Y		
Hedonic model with Zip FE							Y	Y
Observations	1388	2021	2036	907	709	2045	2048	2039
R-Square	0.712	0.237	0.392	0.310	0.276	0.225	0.225	0.400

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Standard errors clustered at the state level are reported in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .



# Estimates are robust to different specifications and controls

## Estimates are robust to tax assessor characteristics

	Dependent variable: Density Growth, 2000-2020							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implicit Land Tax	1.977*** (0.699)	1.551*** (0.365)	1.202*** (0.357)	1.672*** (0.585)	1.455** (0.679)	1.911*** (0.393)	1.764*** (0.421)	1.132*** (0.397)
Effective Property Tax		-5.131*** (1.849)						
CBSA fixed effects	Y							
State fixed effects		Y	Y	Y	Y	Y	Y	Y
Year-2000 controls			Y					Y
Land Use Regulation control				Y				
Land Supply Elasticity control					Y			
Tax Assessor Characteristics						Y		
Hedonic model with Zip FE							Y	Y
Observations	1388	2021	2036	907	709	2045	2048	2039
R-Square	0.712	0.237	0.392	0.310	0.276	0.225	0.225	0.400

This table reports coefficients from county-level regressions of growth in population density on the *implicit land tax*.

Standard errors clustered at the state level are reported in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

# Estimates are robust to different specifications and controls

## Estimates are robust to different hedonic models

	Dependent variable: Density Growth, 2000-2020							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implicit Land Tax	1.977*** (0.699)	1.551*** (0.365)	1.202*** (0.357)	1.672*** (0.585)	1.455** (0.679)	1.911*** (0.393)	1.764*** (0.421)	1.132*** (0.397)
Effective Property Tax		-5.131*** (1.849)						
CBSA fixed effects	Y							
State fixed effects		Y	Y	Y	Y	Y	Y	Y
Year-2000 controls			Y					Y
Land Use Regulation control				Y				
Land Supply Elasticity control					Y			
Tax Assessor Characteristics						Y		
Hedonic model with Zip FE							Y	Y
Observations	1388	2021	2036	907	709	2045	2048	2039
R-Square	0.712	0.237	0.392	0.310	0.276	0.225	0.225	0.400

This table reports coefficients from county-level regressions of growth in population density on the *implicit land tax*.

Standard errors clustered at the state level are reported in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

# Test for alternative explanations

Use differences in timing of the implicit land tax and density to rule out certain types of confounding factors.

1. Look at implicit land tax in the pre-period on density growth in a post-period.
2. Use an instrumental variable design where pre-period implicit land tax is an instrument for the post-period implicit land tax
  - Breaks the link of contemporaneous confounding factors
3. Placebo test, use timing in reverse, post-period implicit land tax on pre-period density growth.

# Tests for alternative explanations using predetermined ILT

The magnitudes suggest little scope for other explanations

	Full Sample				Precise Subsample			
	OLS				IV			
	2010-2020		2000-2020		2010-2020			
Population Density Growth Period	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implicit Land Tax (Pre Period)	0.710*	0.816**	1.628*	1.783***				
	(0.425)	(0.363)	(0.833)	(0.761)				
Implicit Land Tax (Post Sample)					2.712**	6.979***	2.781***	7.031***
					(1.222)	(2.392)	(1.112)	(2.227)
State fixed effects		Y		Y		Y		Y
Observations	1780	1780	1779	1779	1550	1550	1141	1137
R-Square	0.010	0.235	0.012	0.246				
First Stage F Statistic					57.062	32.618	61.094	25.266

# Tests for alternative explanations using predetermined ILT

Instrument current ILT with pre-period ILT limits scope for other explanations

	Full Sample				Precise Subsample			
	OLS				IV			
	2010-2020		2000-2020		2010-2020			
Population Density Growth Period	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implicit Land Tax (Pre Period)	0.710*	0.816**	1.628*	1.783***				
	(0.425)	(0.363)	(0.833)	(0.761)				
Implicit Land Tax (Post Sample)					2.712**	6.979***	2.781***	7.031***
					(1.222)	(2.392)	(1.112)	(2.227)
State fixed effects		Y		Y		Y		Y
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R-Square	0.010	0.235	0.012	0.246				
First Stage F Statistic					57.062	32.618	61.094	25.266

# Placebo tests using reverse timing

Density in the pre-period is not affected by the post-period ILT

	Density Growth, 2000–2010					
	Full Sample			Unstable Subsample		
	(1)	(2)	(3)	(4)	(5)	(6)
Implicit Land Tax (Post Sample)	0.224 (0.562)	0.367 (0.308)	0.233 (0.259)	0.096 (0.554)	0.220 (0.341)	0.188 (0.276)
State fixed effects		Y	Y		Y	Y
Year-2000 controls			Y			Y
Observations	1959	1959	1951	915	915	912
R-Square	0.001	0.218	0.319	0.000	0.235	0.325

This table reports coefficients from county-level regressions of 2000–2010 population density growth on the post-period *implicit land tax*. Estimates in columns 4 through 6 are based on the subsample of counties with post-period *implicit land tax* estimates at least one percentage point different from the pre-period *implicit land tax*. Standard errors, clustered at the state level, are reported in parentheses. \*, \*\*, and \*\*\* indicate significance at the 0.1, 0.05, and 0.001 levels.

# Placebo tests using reverse timing

The effect is even smaller in the unstable subsample where ILT changes between periods

	Density Growth, 2000–2010					
	Full Sample			Unstable Subsample		
	(1)	(2)	(3)	(4)	(5)	(6)
Implicit Land Tax (Post Sample)	0.224 (0.562)	0.367 (0.308)	0.233 (0.259)	0.096 (0.554)	0.220 (0.341)	0.188 (0.276)
State fixed effects		Y	Y		Y	Y
Year-2000 controls			Y			Y
Observations	1959	1959	1951	915	915	912
R-Square	0.001	0.218	0.319	0.000	0.235	0.325

This table reports coefficients from county-level regressions of 2000–2010 population density growth on the post-period *implicit land tax*. Estimates in columns 4 through 6 are based on the subsample of counties with post-period *implicit land tax* estimates at least one percentage point different from the pre-period *implicit land tax*. Standard errors, clustered at the state level, are reported in parentheses. \*, \*\*, and \*\*\* indicate significance at the 0.1, 0.05, and 0.001 levels.

# Land taxes affect other economic variables

Land taxes have positive effects on wages, diversity, and entrepreneurship

Growth in:	Population-weighted density	Wage earnings	Racial diversity (change)	Income diversity (change)	Age diversity (change)	Establishments
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS (full sample, growth from 2000-2020)						
Implicit Land Tax	1.235*** (0.526)	1.932*** (0.599)	0.609*** (0.209)	1.140*** (0.237)	0.355* (0.187)	2.073*** (0.496)
State fixed effects	Y	Y	Y	Y	Y	Y
Observations	2047	2045	2047	2047	2047	2038
R-Square	0.175	0.205	0.146	0.203	0.049	0.263

This table reports coefficients from county-level regressions of growth in various outcomes on the *implicit land tax*. Bootstrapped standard errors, clustered at the state level, are reported in parentheses. \*, \*\*, and \*\*\* indicate significance at the 0.1, 0.05, and 0.001 levels.



# Land taxes affect other economic variables

Land taxes have positive effects on wages, diversity, and entrepreneurship

Growth in:	Population-weighted density	Wage earnings	Racial diversity (change)	Income diversity (change)	Age diversity (change)	Establishments
	(1)	(2)	(3)	(4)	(5)	(6)

Panel B: IV estimates (precise subsample, 2010-2020)

Implicit Land Tax	6.207*** (2.256)	5.979** (2.940)	3.349*** (1.128)	2.854*** (1.075)	0.050 (0.304)	6.913*** (2.211)
State fixed effects	Y	Y	Y	Y	Y	Y
Observations	1550	1549	1550	1550	1550	1550
First-Stage F Statistic	32.618	32.636	32.618	32.618	32.618	32.618

This table reports coefficients from county-level regressions of growth in various outcomes on the *implicit land tax*. Bootstrapped standard errors, clustered at the state level, are reported in parentheses. \*, \*\*, and \*\*\* indicate significance at the 0.1, 0.05, and 0.001 levels.

# What model features are consistent with our findings?

We build a model to investigate the mechanisms, *how do land taxes increase density*.

# Theory

## Model Setting

- Small Open Economy (county)
- Endogenous population level
- Inelastic amount of land for residential purposes

# Theoretical Predictions

An increase in the tax rate on land *can increase density if*

- Tax revenues are rebated to residents (e.g., public goods).
- Some land is owned by absentee landlords.

# Theoretical Predictions: important factors

## Different policy implementations

- An introduction of a tax on land (show you here).
- A substitution from a tax on structures to a tax on land (in paper)
- Downtown and suburban area (in paper).

## Parameters that increase the effect size.

- Population elasticity.
- Elasticity of substitution between land and structures.

## Capitalization of the land tax.

- We assume full capitalization.
- The effects of land taxes are likely **larger** if there is imperfect capitalization.

# Standard setup with fixed land, endogenous population

Utility of household  $j$  over housing  $H_j$  and consumption  $C_j$

$$U_j = H_j^\alpha C_j^{1-\alpha}.$$

Housing is comprised of land  $L_j$  and structures  $S_j$ :

$$H_j = \left( \psi L_j^{\frac{\gamma-1}{\gamma}} + (1-\psi) S_j^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}},$$

# Budget constraint has key assumptions

$$\xi r\bar{L} + \kappa\bar{T} + I_j = rL_j(1 + \tau_L) + p_S S_j(1 + \tau_S) + C_j.$$

1. Land rental income  $\xi r\bar{L}$ , with fraction residential owned land  $\xi \in [0, 1]$ .
2. Tax revenue rebate (or public good)  $\kappa\bar{T}$ , with fraction tax revenues rebated  $\kappa \in [0, 1]$ .
3. exogenous labor income  $I_j$ .
4. Expenditure on land with price  $r$  and land tax  $\tau_L$ ;  $rL_j(1 + \tau_L)$ .
5. Expenditure on structures with price  $p_S$  and structures tax  $\tau_S$ ;  $p_S S_j(1 + \tau_S)$ .
6. Expenditure on the numeraire consumption  $C_j$ .

# Eqm population and structures and land ratio

Population depends critically on land ownership and tax rebates

$$N = \left( \frac{I + \xi r \bar{L} + \kappa \bar{T}}{P} \right)^\epsilon$$

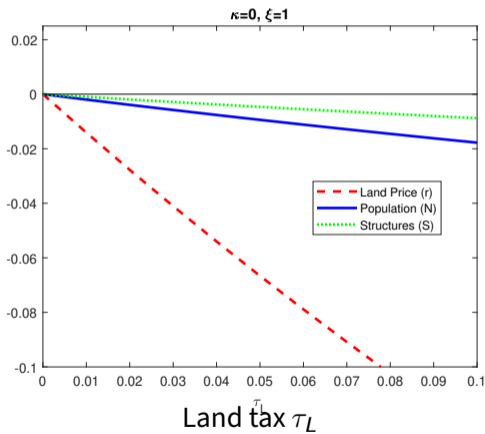
$$\frac{S_j}{L_j} = \left( \frac{1 - \psi}{\psi} \frac{r(1 + \tau_L)}{p_S(1 + \tau_S)} \right)^\gamma$$

Elasticity of population  $\epsilon$  and elasticity of structures and land  $\gamma$  are key parameters.



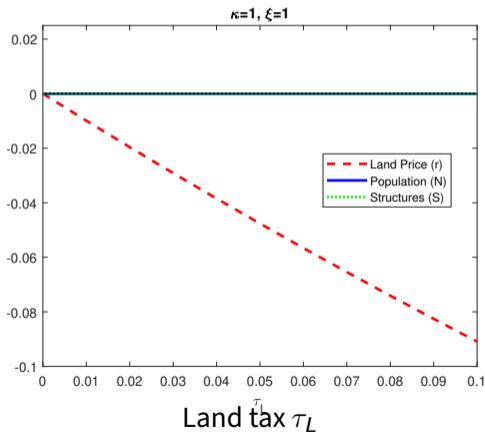
# If tax revenues are confiscated, and land is all locally owned

Land taxes decrease density (blue line decreases), contrary to our findings



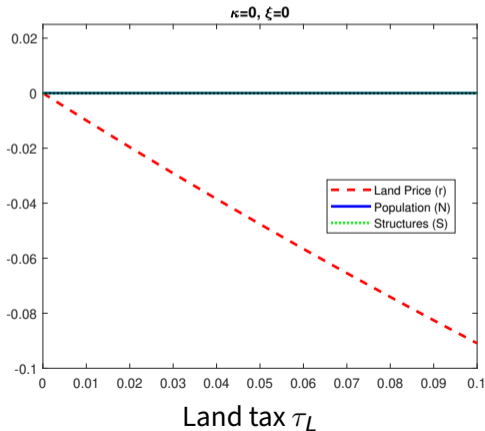
# If land is locally owned and some tax revenues are rebated

Land taxes have no effect on density (blue line flat), contrary to our findings



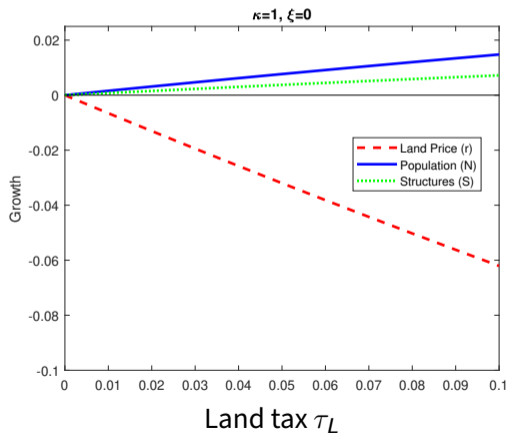
# If tax revenues are confiscated and some land is not owned locally

Land taxes have no effect on density (blue line flat), contrary to our findings



# If tax revenues benefit locally and some land is not locally owned

Land taxes have a positive effect on density (blue line increases), consistent with our findings



# Future work

Should land taxes be implemented in Detroit or San Francisco?

- The effects are larger where the substitution between structures and land is greater (in denser areas), which is what we find.

Feasible implementation mechanisms (see Nick Allen's work).

- Split rate (see Zhou Yang's work).
- Abatement for business structures (Anderson and Dye, 2011; Anderson and Wassmer, 2000)

Land/property as an asset versus market good.

- Option value of land (see John Anderson and Mark Skidmore's work).

# Land taxes might be ok

1. Implicit land taxes exist and are large; 10th percentile is -1.9% and 90th is 0.4%.
2. Implicit land taxes vary across the country.
3. Land taxes lead to higher density, higher employment, higher wage earnings, and more diversity.
4. These effects are due to the land tax effectively raising revenues.



The background features a diagonal split between a teal upper-left section and a light beige lower-right section. The word "References" is centered in the white area between these two colors.

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