IMPLICIT LAND TAXES AND THEIR EFFECT ON THE REAL ECONOMY

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We show empirically that land taxes are associated with higher density, neighborhood diversity, business formation, and other indicators of economic performance. To investigate land taxes empirically, we estimate implicit land taxes (or subsidies) for over 2,000 counties in the U.S. These implicit land taxes arise due to idiosyncratic differences between tax assessors and market valuations of land. We find substantial dispersion in implicit land taxes across U.S. counties and within metropolitan areas and that they are highly persistent within counties. Finally, we develop a model of land taxes and endogenous population to rationalize our results.

KEYWORDS: Land tax.

1. INTRODUCTION

Economists have historically championed the implementation of a land tax based on principles of efficiency, as evidenced by scholarly works such as George (1879), Bentick (1979), Mills (1981), Anderson (1986), Brueckner (1986b), and Anderson (1999). In contrast to modern property taxes, which tax land, improvements, and structures together as

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a bundle, a shift towards levying taxes specifically on land —a concept known as a land tax —holds the promise of fostering economic development and mitigating urban sprawl (Brueckner and Kim, 2003, Banzhaf and Lavery, 2010).[1] With these benefits in mind, recent policy proposals emphasize taxing land to remedy Detroit's urban decline (Anderson et al., 2021). Despite the theoretical benefits of land taxes and the policy interest surrounding them, explicit land taxes are rarely implemented, making their purported merits difficult to assess empirically.[2]

In this paper, we overcome the problem of a lack of explicit land taxes by computing a measure of implicit land taxes. Our measure is based on differences between tax-assessed and market values for land, allowing us to calculate them for most U.S. counties. These implicit land taxes reflect idiosyncratic differences in tax-assessor models, as corroborated by these implicit taxes being uncorrelated with land values and other factors. We document large dispersion in implicit land taxes across U.S. counties and within metropolitan statistical areas and that these taxes are highly persistent within counties. We then use these implicit land taxes to investigate their economic effects and find that they increase density, entrepreneurship, neighborhood diversity, and other measures of economic performance.

Counties in all fifty U.S. states assess property values and levy a tax on the combined value of land and structures (the property tax). We are interested in the effect of a tax only on the value of land, such that two neighboring parcels with the same land value would pay the same tax even if one had a million-dollar structure on it and the other was empty. Although these explicit land taxes are rare in practice, we show that jurisdictions implicitly tax (or subsidize) land when the valuation of land for property tax purposes differs from its market value. Tax assessments and market values tend to differ considerably, as recently documented by Amornsiripanitch (2020), Avenancio-León and Howard (2022), and Berry (2021). We build on this finding and show a mismatch in land valuation. This mismatch causes the property tax to combine an evenly-applied property tax (which taxes land and

[1]Other work has also shown the benefits of land taxes as a source of local public revenue (Arnott and Stiglitz, 1979, Glaeser, 1996).

[2]Notable exceptions include the split-rate taxes enforced in Australia, Denmark, parts of Indonesia, and parts of the U.S. (e.g., Pennsylvania) (Youngman and Malme, 1994, Oates and Schwab, 1997, McCluskey and Franzsen, 2017).

structures the same) and an additional implicit land tax (which taxes only the land value). For example, in jurisdictions where the tax assessment perfectly captures the market value of structures and land, the property tax is evenly applied and there is no implicit land tax. In jurisdictions where the tax assessor *overvalues* land relative to the market, there is an implicit land tax on top of the property, while in jurisdictions where the tax assessor *undervalues* land relative to the market, there is an implicit land subsidy.

Consider the following example of a jurisdiction with a 1% property tax. Tax assessors combine data on the characteristics of a parcel to produce a tax-assessed value for that property. Similarly, buyers value parcels based on some model of the characteristics of a parcel. Suppose the tax assessor and market models of a parcel include the acreage of the parcel—the amount of land. Further, suppose that the tax assessor's model values an additional acre of land at $100,000 while the market model values it at $75,000. Now, consider two identical parcels, except one has an additional acre of land. Suppose the market and tax assessor value the smaller parcel at $500,000. The market will value the larger parcel at $575,000, and the tax assessor will assess it at $600,000. The larger parcel will pay $1,000 more in property tax (0.01 $\times$ $100,000) on a market value only $75,000 more. As a result, the property's effective marginal tax rate will be greater than the statutory marginal tax rate of 1% ($1,000/$75,000 = 1.33%) because the tax assessor values the land more than its market value. In this case, the mismatch between the tax assessor and market models implicitly imposes a land tax of $250, or 0.33%, on top of the 1% property tax.

Our measure of land taxes is based on the implicit and plausibly exogenous idiosyncratic differences in tax assessor and market models. Differences between the tax assessor and market models are likely inadvertent errors in valuation and assessment heuristics. The implicit land tax is a priori independent of characteristics like land values: it is higher in places where the tax assessor values the land more than the market—which occurs in both high– and low–land-value areas. Empirically, we find the the differences between the tax assessor and market models are dispersed spatially but highly autocorrelated within a county. In addition, we find that these differences are not correlated with land prices, racial composition, property value, racial diversity, labor income, number of establishments, land-use regulations, or land supply elasticities.

We estimate implicit land taxes using data on tax-assessed values and sale prices from Zillow's ZTRAX data and ATTOM Data Solutions. This data contains information on 2,750 counties of the U.S.'s 3,243 counties (or equivalents). We use parcel-level data to estimate the tax assessor and market models at a county level. This estimation allows us to recover an implicit land tax for each county.

We use our estimates of implicit land taxes to document several new facts. First, implicit land taxes are substantial, ranging from -3.8% to 4.4%. Second, we find that these taxes are spatially dispersed across the U.S. and within metropolitan statistical areas (MSAs)—consistent with the view that these taxes are exogenous to other factors because they reflect inadvertent errors in tax assessments. For example, the implicit land tax rate varies between -1.4% and 1.8% across the 25 counties within the Atlanta MSA. Third, we find that jurisdictions with higher implicit land taxes have greater growth in density. In particular, a percentage-point increase in the implicit land tax is associated with a 1.9% to 6.6% increase in density and a 1.2% to 6.2% increase in population-weighted density. Finally, we find that jurisdictions with higher implicit land taxes see greater growth in earnings, business establishments, within-county racial diversity, and within-county income diversity.

We provide insights into the mechanisms through which land taxes have these effects by presenting a model in which residential housing developments are produced with land and imported structures. We show that the implications of a land tax depend critically on how land ownership and tax revenues are modeled. For example, with a confiscatory land tax and full residential land ownership, we find no effect of the land tax on other economic factors. In this case, the land tax is fully offset by a land price decline so that the tax-inclusive land cost remains fixed. In contrast, if the tax revenue is rebated to residents (or used to provide public goods), and if some land is owned outside the residential jurisdiction, then the increase in after-tax real income induces an inflow of residents and more building development, consistent with our empirical findings. A tax on structures has the opposite effect. It disincentivizes building structures and increases the cost of housing, resulting in a decline in real incomes and population outflow. Overall, shifting property taxes to land taxes (and away from structure taxes) leads to higher population density. In an extended version of the model with multiple locations within a county, we demonstrate that an increase in the land tax increases population-weighted density.

Our paper provides timely policy insights as cities look to use land taxes to help revitalize. Proponents of a land-value tax in Detroit maintain that it will become a model for Rust Belt cities trying to reverse decades of decline. However, there is a dearth of empirical evidence to validate these claims. To date, the academic literature has provided evidence from Pennsylvania municipalities' experience with split-rate tax systems and Detroit's recent reassessment (Anderson et al., 2021, Alfaro et al., 2021, Hanson, 2021, Yang and Hawley, 2022). We expand on this analysis using our novel measure of implicit land taxes, which allows us to provide U.S.-wide evidence of the broad benefits of land taxes.

Our paper also builds on the literature on the (non-) neutrality of land taxes. Tideman (1982) concludes that a tax on land value is neutral if the land value is defined independently of the improvements on the land. Anderson (1986) demonstrates under what conditions the timing of development is neutral to changes in property taxes —finding in most cases, they are not neutral. Subsequent literature has focused on the timing of development and the role taxes play in the option value of land (Bentick, 1979, Mills, 1981, Anderson, 1993b,a). While we do not model the timing aspect of development, our evidence is consistent with the land tax encouraging density through changes in the option value of land development, as highlighted by this literature.

The remainder of the paper proceeds as follows. Section 2 describes how we measure implicit land taxes. Section 3 discusses the data used to measure implicit land taxes and presents summary statistics across counties. Section 4 uses our measure of implicit land taxes to determine their effect on economic performance. Section 5 puts the empirical evidence in context using a model of land taxation. We conclude in Section 6.

2. MEASURING *IMPLICIT LAND TAXES*

This section outlines how we measure *implicit land taxes* (ILT). The key idea is to use differences in how the market and tax assessors value land to capture implicit and idiosyncratic taxes. One benefit of measuring the *implicit land tax* in this way is that variation across counties is plausibly exogenous—it is based on errors in tax assessor models. We define the *implicit land tax* in subsection 2.1, and we provide examples in subsection 2.2.

2.1. *Defining the implicit land tax (ILT)*

We begin by defining some key variables. Property tax liability T_i at the parcel level i is the product of the statutory tax rate, $\tau_{s,i}$, and the assessed taxable value, A_i,

$$T_i = \tau_{s,i} A_i. \tag{1}$$

The assessed taxable value is determined by the tax assessor's assessment of fair market value and property tax regulations such as homeowner exemptions, assessment ratios (when the assessed taxable value is some fraction of the assessed fair market value), and other property tax assessment limits. We calculate the statutory tax rate at the parcel level by taking the ratio of the property tax liability and the assessed taxable value, which are observed in the data; $\tau_{s,i} \equiv \mathrm{T}_i/\mathrm{A}_i$. We then aggregate the statutory tax rate up to the county level by taking the average of the statutory rates within the county: $\tau_{s,c} = (1/N)\sum_i^N T_i/A_i$, where c denotes county. This measure incorporates all the different counties' jurisdictions, such as libraries, water districts, and community college property tax areas.

The assessed taxable value is a function of property characteristics that differs at the county level c. For concreteness, we model assessed taxable value as a combination of land L_i and structure $S_{j,i}$ characteristics, with indicator variables for neighborhood λ_n,

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

where land is the square footage of land, there are $J-1$ structure characteristics (in our baseline estimates, structure square footage, number of bedrooms, and number of bathrooms), and the neighborhood is given by ZIP code.[3] To select the structure variables, we rely on the LASSO selection operator using 33 variables and their interactions; see Appendix C for more information on model selection and robustness.[4] We observe $A_{i,c}$, L_i, $S_{j,i}$, and λ_n in the data and estimate the county-specific coefficients $\beta_{j,c}$.

[3] In talking with county tax assessors, this process is very similar to what happens in practice. For example, one county assessor for a large Utah county told us he works with two academics who run machine learning hedonic models to estimate tax assessments.

[4] The variables the LASSO model chooses include attic square footage, architecture code, finished basement, basement square footage unfinished, central air, exterior type, indicator for a fireplace, foundation type, garage square footage, garage type, heat type, number of one-quarter bathrooms, number of half bathrooms, number of three-quarter bathrooms, number of full bathrooms, number of bedrooms, number of stories, number of units, patio and porch type, privacy type, square footage of the structure, structure type, year built, effective year built, number of car garage, number of structures, construction quality, structure condition, roof type, number of fireplaces, a pool indicator, and year of remodeling.

The market value is similarly a function of property characteristics that differ at the county level c. We similarly model the market value, including neighborhood fixed effects ϕ_n,

$$M_{i,c} = \delta_{0,c} + \delta_{1,c} L_i + \sum_{j=2}^{J} \delta_{j,c} S_{j,i} + \phi_n + \nu_i, \tag{3}$$

where land, structure characteristics, and neighborhood are the same as in equation (2), but the coefficients are different. For market value, we use sales prices in our baseline estimates. We also provide estimates using imputed market value based on the Federal Housing Finance Agency's (FHFA) annual ZIP code-level indices and a machine learning algorithm (see Appendix B for more details). We calculate the effective tax rate $\tau_{e,c}$ as the average of the ratios of property taxes paid to the market value of a parcel; $\tau_{e,c} = (1/N)\sum_i^N T_i/M_i$. The coefficients on the property characteristics are allowed to differ across counties and between the assessed taxable value and the market value equations. The market value equation is a standard hedonic model with foundations from Waugh (1929) and Rosen (1974). We follow the advice of Bishop et al. (2020) in estimating these hedonic models. For example, Kuminoff et al. (2010) discusses the benefits and costs of using neighborhood fixed effects such as ZIP code indicators to mitigate omitted-variable bias. In our analysis, we provide estimates with and without these fixed effects and find similar estimates.[5] McMillen and Thorsnes (2003) and McMillen and Redfearn (2010) discuss the benefits of nonparametric and time-varying methods. Our analysis estimates our models in different time subsets to test for time consistency. We provide more details on the hedonic method and our selection of variables in Appendix C. We also report in Appendix C estimates from 30 additional hedonic models using different variables and interaction terms in a subset of the data and find similar estimates. The novel aspect of our hedonic estimation is using both market and assessed-taxable-value equations and differences in these coefficients. As we show, us-

[5]The inclusion of neighborhood fixed effects has implications for the interpretation of the land slope coefficients $\beta_{1,c}$ and $\delta_{1,c}$. Within-county differences in land prices could reflect within-county differences in neighborhood amenities. Neighborhood fixed absorb these differences in neighborhood amenities such that —if the lot size is correlated with neighborhood amenities —$\beta_{1,c}$ and $\delta_{1,c}$ capture the marginal effect of land size only. However, the neighborhood fixed effects also absorb average differences in lot size across neighborhoods that are useful for identifying the slope coefficient.

ing differences in these equations allows us to construct idiosyncratic parameters that are independent of confounding factors.

We define the *implicit land tax* rate using these definitions. Specifically, we decompose the property tax into four components: the level of property taxes (given by the effective tax rate times the market value), the *implicit land tax*, the implicit structures tax, and implicit level differences across counties and neighborhoods. To decompose the property tax, we start with equation (1) and add and subtract $\tau_{e,c}M_i$ (the level of property taxes in terms of the market value) and expand based on equations (2) and (3),

$$
\begin{aligned}
T_{i,c} &= \tau_{s,i}A_i \qquad (4)\\
&= \tau_{e,c}M_i + \tau_{s,i}A_i - \tau_{e,c}M_i\\
&= \tau_{e,c}M_i + \tau_{s,i}(\beta_{0,c} + \beta_{1,c}L_i + \sum_{j=2}^{J}\beta_{j,c}S_{j,i} + \lambda_n + \varepsilon_i) - \tau_{e,c}(\delta_{0,c} + \delta_{1,c}L_i + \sum_{j=2}^{J}\delta_{j,c}S_{j,i} + \phi_n + \nu_i).
\end{aligned}
$$

Next, we rearrange the equation by grouping terms that augment land and structures. We then take the expectation of the tax payment under the assumption that tax-assessed values and statutory tax rates are independent. This allows us to decompose the property tax payment into four components: the level of property tax $\tau_{e,c}M_c$, the *implicit land tax* with tax rate ILT_c, the *implicit structures tax* with tax rate IST_c, and differences in the constant terms and fixed effects θ,

$$
\begin{aligned}
E[T_i] &= \tau_{e,c}M_c + \frac{\tau_{s,c}\beta_{1,c} - \tau_{e,c}\delta_{1,c}}{\delta_{1,c}}\delta_{1,c}L_c + \sum_{j=2}^{J}\frac{\tau_{s,c}\beta_{j,c} - \tau_{e,c}\delta_{j,c}}{\delta_{j,c}}\delta_{j,c}S_{j,c} + \theta \qquad (5)\\
&= \tau_{e,c}M_c + ILT_c\delta_{1,c}L_c + \sum_{j=2}^{J}IST_{j,c}\delta_{j,c}S_{j,c} + \theta,
\end{aligned}
$$

where $\theta \equiv \tau_{s,c}\beta_{0,c} - \tau_{e,c}\delta_{0,c} + \lambda_n - \phi_n,\ E[M_i] = M_c,\ E[L_i] = L_c,\ E[S_{j,i}] = S_{j,c}$, and $E[\varepsilon_i - \nu_i] = 0$.

This decomposition separates the *implicit land tax* from the level of property taxes (given by the first term). Implicitly, then, the last three terms net to zero. Said differently, if the tax assessor overvalues land (creating a land tax), they must undervalue some structures or the entry fee (given by the difference in constant terms). In Section 5, we consider the theoretical implications of a land tax substituting for other elements of the property tax —and, separately, the effects of a land tax above and beyond taxes on different aspects of the property.

Our focus is the *implicit land tax* rate:

$$\mathrm{ILT}_c = \frac{\tau_{s,c}\beta_{1,c} - \tau_{e,c}\delta_{1,c}}{\delta_{1,c}}, \tag{6}$$

which can be positive or negative depending on whether the tax assessor over-values or under-values land relative to the market. We write the *implicit land tax* as a rate of the value of land $\delta_{1,c}L_{i,c}$, which is why $\delta_{1,c}$ is in the denominator. Writing the *implicit land tax* as a rate is helpful for comparison across counties where land values vary dramatically. The *implicit land tax* depends on the statutory and effective tax rates and the tax-assessed and market-model parameters. The *implicit land tax* increases with the statutory tax rate and tax-assessed value of land, $\beta_{1,c}$ and decreases with the market value of land $\delta_{1,c}$ and the effective tax rate. The *implicit land tax*, therefore, is characterized by differences in the tax-assessed and the market models of value.

2.2. *Implicit land tax examples*

Several examples provide intuition that motivates modeling tax liability as in equation (5). First, consider the idealistic and unrealistic case in which the assessed taxable value model is the same as the market model (e.g., $\beta_1 = \delta_1$ and $A_i = M_i$). In this case, the effective tax rate is equal to the statutory rate $\tau_{e,c} = \tau_{s,c}$. The *implicit land tax*, in this case, is zero (see equation 6). Put another way, there is no land tax or subsidy without idiosyncratic differences in the tax assessor and market model.

Second, consider the case where the market value is equal to the assessed taxable value on average, but the coefficients differ. Said differently, the tax-assessed model is correct overall but not for each component. In this case, the statutory and effective tax rates are the same, and the *implicit land tax* can be written as $ILT_c = \tau_{s,c}\left(\beta_{1,c}/\delta_{1,c} - 1\right)$. This example highlights how, when the tax assessor values land more than the market ($\beta_{1,c} > \delta_{1,c}$), there is a land tax, and how when the tax assessor values land less than the market ($\beta_{1,c} < \delta_{1,c}$), there is a land subsidy.

FIGURE 1.—*Implicit land tax* examples

FIGURE 1.—Notes: This figure provides stylized examples of changes in tax payments as lot size increases. For expositional ease, the subscripts on the coefficients have been omitted, such that $\beta_{1,c}$ is simply written as β and $\delta_{1,c}$ is written as δ.

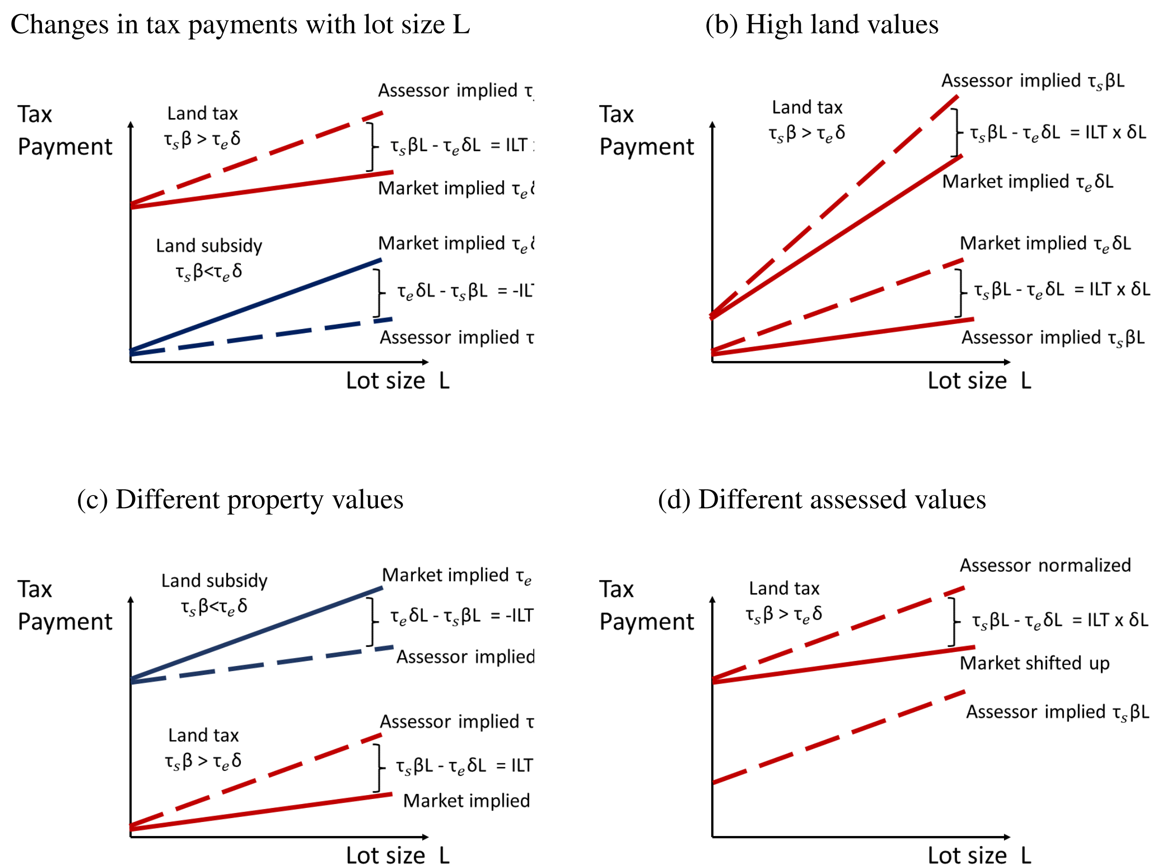


Figure 1 depicts the relationship between tax payments and lot size holding fixed structural characteristics. The dashed line depicts changes in tax payments as tax assessed value increases due to increases in lot size. The sold line depicts how much tax payments would increase with lot size if they were based on market values. Some panels consider two counties (Red and Blue) to highlight differences. In Panel A, the market and tax-assessed tax payment lines for the Red county are above those in the Blue County, indicating that properties are more valuable in the former. In the Red County, the tax-implied line has a steeper slope than the market-implied slope, indicating that property taxes increase more with the amount of land a property has than the market value of the land would imply. This difference in slopes creates an *implicit land tax*. In the Blue County, the tax-implied line has a flatter slope, indicating that property taxes increase less with the amount of land a property has than the market value of the land would imply. This difference in slopes creates an implicit land subsidy.

We use Figure 1 to demonstrate that the *implicit land tax* is independent of county-level land prices, the level of the property values, and differences between tax-assessed property values and market property values. Panel B demonstrates the (non)-influence of higher county-level land values. This panel depicts alternative (high and low) land prices in the Red county, reflected in the steepness of market-implied and tax-assessed lines. However, the relative slopes of the lines have remained fixed, and thus, the land tax for the Red County is the same as depicted in Panel A.

Panel C demonstrates the (non)-influence of relative property values. In the baseline example of Panel A, the Red County had higher property values than the Blue County (on average, given the higher y-intercept), and the Red County had a land tax. In Panel C, the Blue County has higher (average) property values but continues subsidizing land (a negative ILT). Therefore, the *implicit land tax* does not depend on a county's average level of property values.

Panel D demonstrates the (non)-influence of different property valuations by the tax assessor and market. In the previous panels, the tax-assessed property values (absent land) match market property values in each county, depicted by the identical y-intercepts. In Panel D, we provide an example where the tax assessor has a lower valuation of the property absent land than the market, indicated by the lower y-intercept. To find the land tax, we must first normalize the y-intercept and then take the difference between the two lines. We can see that the land tax in Panel D is the same as in Panel A, even though the y-intercept is different for the tax assessor in Panel D. This case works similarly well for land subsidies and shifts up and down of the y-intercept.

Figure 1 highlights the types of potential confounding factors that would and would not be problematic for our estimation. We may be concerned that *implicit land taxes* are systematically higher in counties with higher land values (e.g., due to higher amenities). This figure demonstrates, however, that this type of confounding factor is not an issue because our land tax estimate is independent of the land value. Consistent with the intuition in the figure, our estimates of land values (captured by δ_1) are not substantially positively or negatively correlated with the *implicit land tax* (Appendix Table E.1). Similarly, the *implicit land tax* is not substantially correlated with initial values of the share of the population that is white, property value, density, population-weighted density, racial diversity, labor income, establishments, land use regulations, or land supply elasticities (Appendix Table E.1).

We may also be concerned that counties with higher land supply and/or housing productivity have lower property values and density. However, this figure demonstrates that our land tax estimate is independent of the level of the property value. Empirically, we find evidence consistent with this intuition, as the *implicit land tax* is not correlated with county-level property values, land supply elasticities, or housing productivity (Appendix Table E.1).

Another potential concern is tax assessors shifting their assessments down for all properties to avoid excessive appeals. This level shift does not affect our land tax estimation because it does not affect the relative slopes of the market and tax-assessor lines. Consistent with this intuition, we find no relationship between the *implicit land tax* and assessor characteristics, such as whether a county's tax assessor is elected or appointed (Panel A of Appendix Table E.2).

More generally, the factors that could confound our analysis are determinants of property value and tax assessment *differences* that are correlated with changes in economic outcomes. For example, growing counties might be more likely to outsource their tax assessments to vendors. Our estimates would be biased if a vendor that is likely to provide assessments in growing counties also systematically overvalues land relative to the market. We tested for this type of violation and found no evidence for it. As we discuss below, our estimates are robust to estimating them in the subset of counties where the *implicit land tax* is consistent over time—limiting the potential influence of a tax assessment change in response to economic growth. And, as discussed above, we find no evidence that tax assessor models that overvalue land are systematically related to key factors such as using a computer hedonic model or having elected tax officials (Appendix Table E.2). We also find that the *implicit land tax* is not systematically correlated with initial values of variables of interest, including land price, the share of the population that is white, property value, density, population-weighted density, racial diversity, labor income, establishments, land use regulations, or land supply elasticities (Appendix Table E.1).

3. DATA

3.1. *Real estate data*

We use data from Zillow's Transaction and Assessment Database (ZTRAX) and ATTOM Data Solutions to create a panel of parcel-level data between 2006 and 2016. Zillow and ATTOM collect this data from county deeds in more than 2,750 of the 3,243 counties (or equivalents) in the United States. This data includes records for 374 million parcels and includes information on property taxes paid, sales price, tax assessed value, and a series of parcel characteristics—including lot size, square footage, number of bedrooms, and number of bathrooms. Gindelsky et al. (2022) provide a detailed description of the Zillow data and comparisons with Census data, and we provide more details on the sample construction in Appendix A.

We are interested in differences between market and tax-assessed value of the land. Capturing these differences requires sufficient observations in which all of these variables are populated. This limits our sample to counties with sufficient transactions with the required data on parcel characteristics; specifically, we use 30 parcel sales per county over ten years. This restriction yields *implicit land tax* estimates for many counties while limiting the inclusion of counties with imprecisely estimated *implicit land taxes*. Among our resulting sample, approximately 90% of counties exhibit precise estimates, with standard errors of less than 0.02.[6]

We provide estimates using two different samples. The first uses sales prices for the market value. The advantage of this sample is that it measures the market price from observable sales without any additional estimation. The disadvantage of this sample is that it comprises a smaller number of parcels, and there may be concerns about the selection of parcels that sell. The second sample imputes market values using the Federal Housing Finance Agency's (FHFA) annual ZIP code-level indices and a machine-learning hedonic model following Bradley et al. (2023) (see Appendix B for more details). For parcels with a sale, we extrapolate market values in years they did not sell using the FHFA annual ZIP

[6]We compute standard errors for each county-level *implicit land tax* using the delta method.

code-level indices. We average the extrapolated values if a parcel sells more than once in our sample. For parcels without a sale, we use a hedonic model based on machine learning models following Bradley et al. (2023). The benefit of the hedonic model is that we can estimate a market price for parcels without a sale if it has data on characteristics. The limitation of computing *implicit land taxes* using machine learning is that the imputation of market values may introduce measurement errors in our estimates.

Our analysis examines the effects of *implicit land taxes* on growth in economic outcomes from either 2000 or 2010 through 2020. To help further address any concerns that *implicit land tax* rates are responding to changes in economic conditions, we separately estimate *implicit land tax* rates during an *early period* (2006-2013) and a *latter period* (2013-2016) parts of the sample. We use 2013 as the threshold to balance the observations; even so, we are limited to 1,792 counties with sufficient coverage in the early period to estimate the *implicit land tax*.

In the process of estimating county-level *implicit land taxes*, we also estimate county-level marginal land prices ($\delta_{1,c}$). Davis et al. (2021) recently provided county-level estimates of land prices, and it is reassuring that our land price estimates are positively correlated with theirs (t-stat 7.01) despite differences in underlying methodology and interpretation. For example, our land price captures the intensive margin of expanding lot size within a county, whereas the Davis et al. (2021) estimate includes both the intensive margin and the extensive margin value of living in a county.[7]

3.2. *Estimates of the implicit land tax*

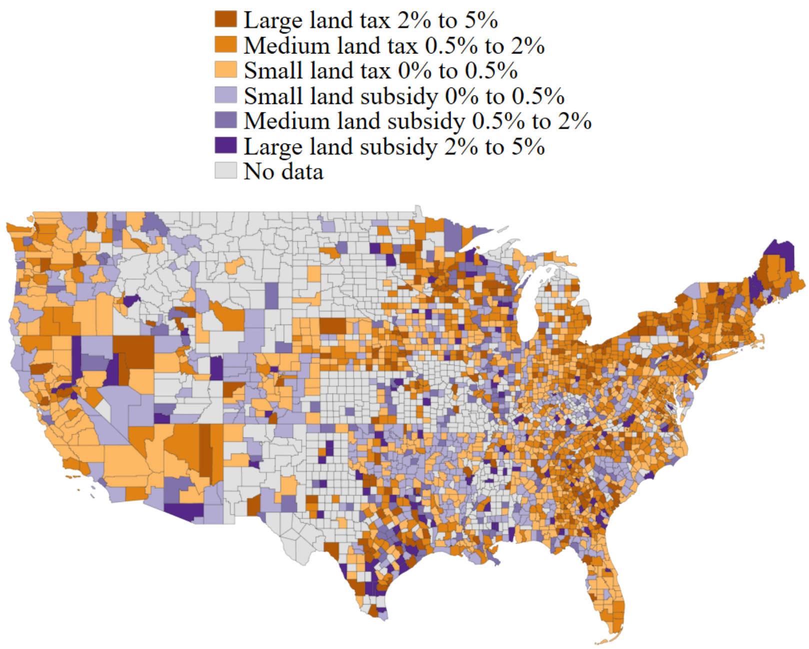
Our *implicit land tax* estimates exhibit substantial dispersion. The extreme values in our distribution are also the least precisely estimated. To limit the influence of extreme (and imprecisely estimated) *implicit land taxes*, we trim our sample at the 5th and 95th percentiles. After this trimming, the *implicit land tax* across the 2,071 remaining counties ranges from -3.8% to 4.4%.

Figure 2 reports the spatial dispersion in our *implicit land tax* estimates. Our sample is concentrated where there is more population because those areas have better data coverage and home sales. Counties colored purple subsidize land. The darkest purple indicates

[7] In our analysis, the extensive margin is captured by $\delta_{0,c}$ plus neighborhood fixed effects ϕ_n.

FIGURE 2.—Spatial Dispersion of the *implicit land tax*

FIGURE 2.—Notes: This figure depicts our land tax estimates by county. Counties in orange indicate a land tax, with the darkest orange having a land tax between 2% and 5%. Counties in purple indicate a land subsidy (negative land tax), with the darkest purple having a land subsidy between 2% and 5%. The gray counties are those with insufficient data to estimate the land tax.



a subsidy of 2-5%, the lighter purple indicates a subsidy of 0.5-2%, and the lightest purple indicates a subsidy of 0%-0.5%. Counties colored orange tax land. The darkest orange indicates a tax of 2-5%, the lighter orange indicates a tax of 0.5-2%, and the lightest orange indicates a tax of 0%-0.5%. The high level of dispersion of *implicit land taxes* and subsidies support the notion that *implicit land taxes* are due to idiosyncratic differences in tax assessment models.

Implicit land taxes vary across the country and within more condensed geographies. Table I reports the counties that exhibit the largest land tax and subsidy (most negative *implicit land tax*). Table II reports summary statistics for the *implicit land tax* and the effective property tax rate for the sales-only sample and machine-learning sample. The *implicit land tax* estimates range from -1.9% to 0.06% at the 10th and 90th percentiles of the distribution in the sales-only sample. As a point of comparison, the 10th and 90th percentiles of the effective property tax estimates are 0.0% and 0.9%. There is more variation in *implicit land* *tax* than the effective property tax, as seen by the standard deviations reported in column 3. Specifically, the standard deviation for *implicit land tax* is 0.011, and for the effective property tax, it is 0.004. Figure 3 shows the full distribution of the *implicit land tax* in both the sales-only and machine-learning samples. The *implicit land tax* varies across the country and within CBSAs. Table III reports the within-CBSA dispersion in *implicit land taxes* among CBSAs for which we have estimates from at least eight counties.

TABLE I

COUNTIES WITH LARGEST *Implicit 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-Waukesha-West Allis, WI	Wisconsin	-0.038	0.004
	Coryell	Killeen-Temple-Fort Hood, 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	Minneapolis-St. Paul-Bloomington, MN-WI	Minnesota	0.044	0.001

Notes: This table reports the *implicit land tax* and the effective property tax for the ten counties with the largest land subsidy (top rows) and the ten counties with the largest *implicit land tax* (bottom row).

TABLE II

SUMMARY STATISTICS

	Mean	Median	SD	p10	p90
	(1)	(2)	(3)	(4)	(5)
Estimates based on Sales Only					
Implicit Land Tax (ILT)	-0.006	-0.006	0.011	-0.019	0.006
Effective Property Tax (EPT)	0.004	0.003	0.004	0.000	0.009
Estimates based on Machine Learning					
Implicit Land Tax (ILT)	-0.006	-0.006	0.011	-0.019	0.007
Effective Property Tax (EPT)	0.005	0.004	0.004	0.001	0.009
Growth in outcome variables, 2000-2020					
Density	0.074	0.043	0.177	-0.120	0.312
Population-weighted density	0.022	0.005	0.162	-0.171	0.230
Racial diversity	0.183	0.178	0.087	0.079	0.294
Income diversity	0.080	0.071	0.084	-0.001	0.187
Age diversity	0.006	0.006	0.039	-0.017	0.031
Earnings	0.578	0.571	0.269	0.257	0.896
Establishments	0.024	-0.006	0.206	-0.199	0.306

Notes: This table reports summary statistics for the counties in the trimmed sample of the *implicit land tax*. Population density is based on U.S. Census data, total labor earnings is based on Quarterly Census of Employment and Wages data, neighborhood diversity is based on Census data and calculated as an entropy measure, and business establishment formation is based on County Business Patterns data.

FIGURE 3.—Histogram of *implicit land taxes*

FIGURE 3.—Notes: This figure provides a histogram of the implicit land tax in the sales only sample (gray bars) and machine learning sample (red rectangles). The horizontal axis indicates that the *implict land tax* varies between -4% to 4.4%.

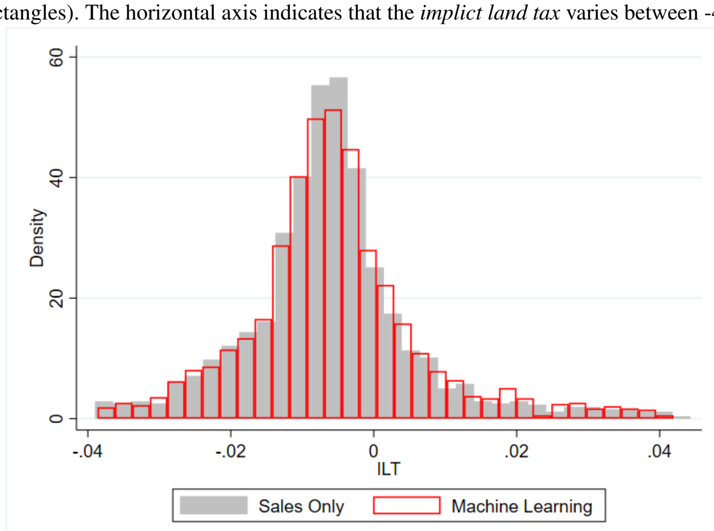


TABLE III

WITHIN-CBSA DISPERSION IN THE *implicit land tax*

CBSA	Number 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

Notes: This table reports the mean and standard deviation of the *implicit land tax* for CBSAs with at least eight counties that have *implicit land tax* estimates.

3.3. *Economic Outcomes*

We combine our *implicit land tax* estimates with a range of county-level economic outcomes for each decade since the year 2000. These outcomes include population density (based on U.S. Census data), total labor earnings (based on Quarterly Census of Employment and Wages data), neighborhood diversity (based on Census data), and business establishment formation (based on County Business Patterns data).

We consider both changes in density and population-weighted density. Changes in density could reflect a higher concentration of the population at the county's population center or sprawl associated with the dispersion of the population center (Brueckner and Kim, 2003). Therefore, we also examine population-weighted density, which is the population-weighted average of census-tract–level population density within each county. Growth in population-weighted density indicates a concentration of the population, whereas a reduction indicates sprawl.

We also consider changes in neighborhood diversity, including income, racial, and age diveristy. We construct a county-level measure of racial entropy (diversity) following White (1986) and used by Heath et al. (2023). First, we create census-tract–level measures

$$H_i = -\sum_{j=1}^{k} p_{ij} \log p_{ij}, \tag{7}$$

where p_{cj} is the population of group j in tract i, and j indexes five racial groups: Asian, Black, Hispanic, Other, and white. Tracts with higher index values are more racially diverse. We then compute county-level entropy as the population-weighted average of census-tract-level entropy. Income diversity and age diversity are defined similarly.

Summary statistics for these outcome variables are reported in Table II. To remove the potential influence of extreme values, we winsorize all outcomes at the 1% and 99% levels. In our sample, density increased by 7.4% from 2000 to 2020 (column 1), with a standard deviation of 17.7% (column 3). The distribution of the growth in density is skewed positive, as the median is only 4.3% (column 2), and the 10th percentile and 90th percentile are -12.0% and 31.2%, respectively (columns 4 and 5). Increases in density tended to be larger than increases in population-weighted density. We also find a positive trend in diversity and earnings. Diversity (racial entropy) increased by 18.3% between 2000 and 2020. Nominal earnings increased by 57.8% on average.

4. RESULTS

4.1. *Empirical specifications*

This section uses the *implicit land tax* estimated in Section 2 to estimate the effects of land taxes on growth in population density from 2000 to 2020, and on other economic outcomes, $\%\Delta Y_c$. In this subsection, we explain our baseline empirical specifications, our robustness specifications, our specifications to rule out types of confounding factors (including an instrumental variable design), and finally placebo specifications to investigate spurious correleation. We discuss the estimates in the following subsection.

In our baseline specification, we include state fixed effects α_S and controls X_c to add precision and to account for potential confounding factors. The effect of the *implicit land tax* is given by γ in the specification,

$$\%\Delta Y_c = \alpha_S + \gamma \mathrm{ILT}_c + X_c \Gamma + e_c. \tag{8}$$

We report bootstrapped standard errors clustered at the state level to account for our generated regressor and variation at the state level.[8]

Our baseline specification relies on the *implicit land tax* being idiosyncratic and exogenous due to inadvertent differences in tax assessor and market models. This condition seems plausible and is consistent with our finding that the *implicit land tax* is not correlated with a host of factors we could be concerned about (see Appendix Table E.1). To further investigate this identification assumption, we provide several additional specifications. First, we consider subsets of counties where the effect of the *implicit land tax* should be larger and less likely to be driven by spurious correlations. The first subset is counties where the *implicit land tax* is similar when we estimate it in the pre- and post-periods. The second

[8] Our bootstrap is done in two steps. First, properties are sampled (with replacement) within counties to estimate the *implicit land tax*, producing a sample of *implicit land tax* estimates. Second, we sample states (with replacement) and estimate the model in equation 8. This two-step procedure uses 5,000 bootstrap samples and captures the variability in both the *implicit land tax* and model fit and is more conservative than sampling only once.

subset is counties where the *implicit land tax* is precisely estimated. We then also provide estimates with both restrictions. We report these estimates in our baseline table, Table IV.

Second, we consider the robustness of our estimates to a wide array of control variables and estimates of the *implicit land tax* with different hedonic models. To isolate potential confounding factors, we consider CBSA fixed effects, controls for economic conditions in the year 2000, land use regulations, land supply elasticities, and tax assessor characteristics. To isolate effects due to the calculation of the *implicit land tax*, we consider estimates where we estimate the *implicit land tax* with a different hedonic model that includes ZIP code fixed effects. We report these estimates in Table V, and in Appendix C, we consider 30 additional hedonic models.

Third, we consider differences in time to rule out several forms of confounding factors. These specifications estimate the effect of the *implicit land tax* calculated in a pre-period on the growth in population density in a post-period (2010–2020),

$$\%\Delta Y_c^{\text{POST}} = \alpha_S + \gamma \text{ILT}_c^{\text{Pre}} + X_c\Gamma + e_c. \tag{9}$$

In these specifications, the *implicit land tax* is pre-determined with respect to economic conditions, which prevents those factors from influencing the *implicit land tax*. These specifications rely on the *implicit land tax* being consistent through time such that the *implicit land tax* measured in the pre-period is correlated with the *implicit land tax* in the post-period. We further explicitly exploit the relationship between pre and post-period measures of the *implicit land tax* by using the pre-period *implicit land tax* as an instrumental variable for the post-period *implicit land tax*. The first- and second-stage regressions in this instrumental variable (IV) design are

$$\begin{aligned} \text{ILT}_c^{\text{Post}} &= \alpha_{S1} + \gamma_1 \text{ILT}_c^{\text{Pre}} + e_1 \\ \%\Delta Y_c^{\text{POST}} &= \alpha_{S2} + \gamma_2 \widehat{\text{ILT}_c^{\text{Post}}} + X_c\Gamma + e_2, \end{aligned} \tag{10}$$

where $\widehat{\text{ILT}_c^{\text{Post}}}$ is the predicted value from the first stage. We report these estimates in Table VI.

Finally, we provide placebo specifications to rule out additional spurious correlation between our estimates of the *implicit land tax* and changes in population density. These placebo specifications estimate the effect of the *implicit land tax* calculated in the post-period on growth in population density in the pre-period. We further refine this test by using the subsample of counties where the *implicit land tax* in the pre-period differs from the estimate in the post-period. These specifications capture potential spurious correlations in the absence of the effect of the *implicit land tax*. A small and statistically insignificant effect in these specifications, therefore, limits the potential for these confounding factors to explain our results. We report these estimates in Table VII.

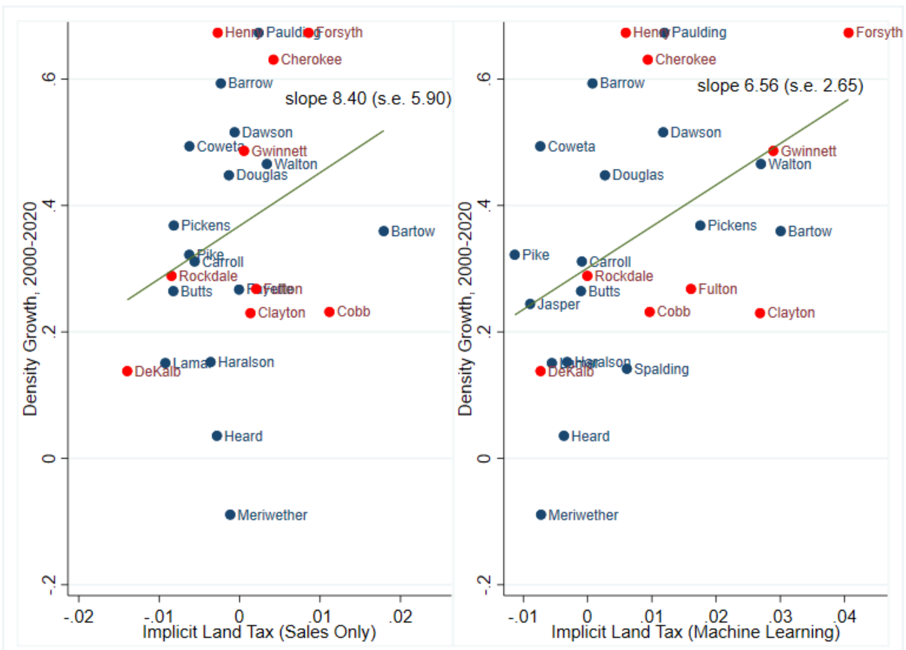
4.2. *Land taxes and density*

We begin with an example of the relationship between density and *implicit land taxes* in the greater Atlanta, GA, metropolitan statistical area, where we have data for many counties. Figure 4a documents, within the Atlanta MSA, a strong relationship between *implicit land taxes* and growth in population density from 2000 to 2020. For example, Jasper County has a roughly 1% subsidy of land and experienced a roughly 24% increase in density. In comparison, Dawson County has a 1% land tax and experienced a roughly 50% increase in density. We find the positive relationship between the *implicit land taxes* and density holds more broadly. Specifically, the binscatter plot across all counties in our sample in Figure 4b exhibits a clear positive relationship. Further, these relationships hold in both the sales-only (reported on the left) and machine-learning (reported on the right) samples.

FIGURE 4.—Implicit land taxes and density

FIGURE 4.—Notes: This figure graphs the relationship between *implicit land taxes* and density growth from 2000 to 2020. Panel a considers the relationship within Atlanta, GA. Each dot represents a county (red for urban counties and blue for rural/suburban counties). Panel b considers the relationship across all counties in our sample. Each dot represents many counties, as this is a binscatter plot. In each panel, the graph on the left uses the sales only sample and the graph on the right uses the machine learning sample.

Implicit land taxes and density in Atlanta, GA



(b) Implicit land taxes and density in the US

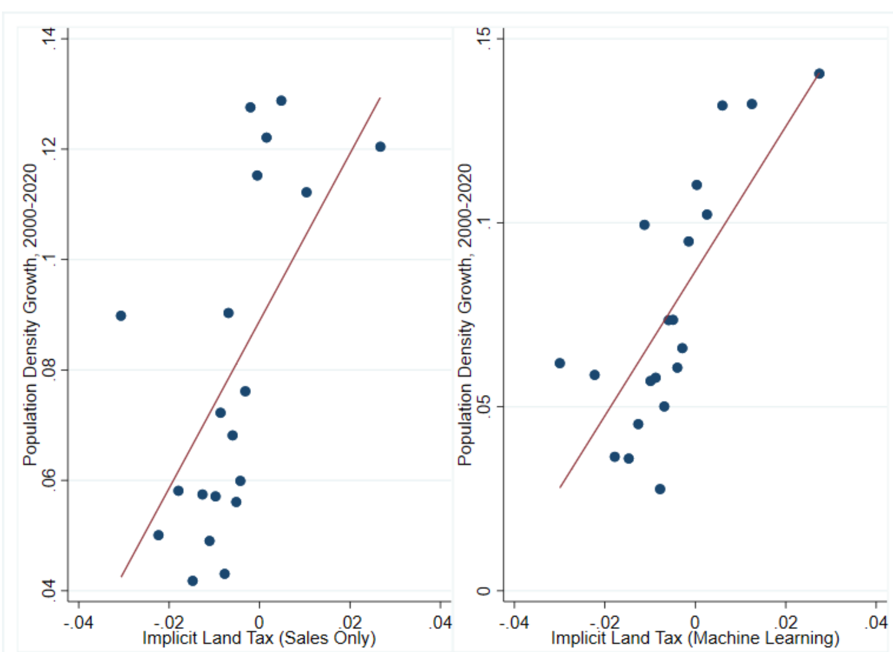


FIGURE 4.

Regression evidence Table IV reports the regression estimates of the effect of the *implicit land tax* on density growth between 2000 and 2020 from our baseline specifications in equation (8). We find that a one-percentage-point increase in the *implicit land tax* is associated with a 1.48% increase in population density growth, reported in column 1. The estimate is larger at 1.92% when including state fixed effects (column 2), highlighting the importance of within-state variation in the *implicit land tax*. These estimates are statistically significant at the 1% level, where bootstrapped standard errors clustered at the state level are reported in parentheses under the estimates.

TABLE IV

Implicit land tax AND POPULATION DENSITY

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***	1.919***	2.849***	3.589***	2.682***	3.081***	4.646***	6.618***
	(0.622)	(0.396)	(0.927)	(0.956)	(0.834)	(0.725)	(1.346)	(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
Panel B: Machine Learning								
Implicit Land Tax	1.679**	1.890***	2.334***	2.484***	2.109*	2.557***	3.128***	3.620***
	(0.766)	(0.713)	(0.923)	(1.021)	(1.084)	(0.824)	(1.199)	(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

Notes: This table reports coefficients from county-level regressions of growth in population density on the *implicit land tax* given in equation (8). We report bootstrapped standard errors, clustered at the state level, in parentheses. *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Refining the sample to stable and precise counties In columns 3 through 8 of Table IV, we report estimates where we refine the sample to investigate the potential for measurement error from estimating the *implicit land tax* to attenuate downward the estimated effects on density. One way to mitigate this attenuation is to limit the sample to counties for which we have stable and precise *implicit land tax* estimates. The tradeoff is that we limit our observations. To understand the nature of this tradeoff, we examine subsamples of the data for which we have stable and precise *implicit land tax* estimates.

We restrict the sample to counties with stable *implicit land tax* estimates in columns 3 and 4—*pre-period* and post-period *implicit land tax* estimates within 0.01 of each other. This sample restriction helps mitigate endogeneity concerns by removing counties for which the *implicit land tax* may have changed in response to population growth. As expected, the estimated effect of the *implicit land tax* is larger using this stable subsample.

We restrict the sample to counties with precise *implicit land tax* estimates in columns 5 and 6—those with standard errors less than 0.01. These estimates mitigate the potential influence of measurement error. As expected, the *implicit land tax* has much stronger estimated effects using this precise subsample than using the full sample in columns 1 and 2.

Finally, we restrict the sample to the stable and precise subsamples in columns 7 and 8. The estimated effects of the *implicit land tax* are larger and they remain statistically significant despite the reduced number of observations.

Imputed market value sample In Panel B of Table IV, we report estimates with market values, imputed using the Federal Housing Finance Agency's (FHFA) annual ZIP code-level indices and machine-learning estimates (for details see Appendix B). Differences in point estimates from the machine-learning sample may arise from differences in the sample (homes that sell versus homes with data on home characteristics) or home values from the machine-learning model. Generally, the estimates are relatively similar between our measures based on home values from sales or the machine-learning model (Panel A compared to Panel B). For example, in our baseline estimates with state-fixed effects in column 2, the sales-only estimate is 1.92% and the machine learning estimate is 1.89%. As a result, to limit potential measurement errors that could be introduced by the machine-learning model, the remaining analysis focuses on the *implicit land tax* computed with the market value of observed sales (rather than the imputation).

Robustness In Table 5 columns 1 through 3, we report estimates where we assess the robustness of our results by including various controls and examining additional measures of the *implicit land tax*. We include CBSA (rather than state) fixed effects in column 1. The *implicit land tax* exhibits strong effects within CBSAs (consistent with the evidence for Atlanta from Figure 4a). In column 2, we include the effective property tax rate (EPT) as a control. As expected, a higher effective property tax rate is associated with reduced density. Consistent with the relative independence of the *implicit land tax* and effective property tax rate, the estimate of the effect of the *implicit land tax* remains strong.

We include controls measured in 2000 in column 3. These controls include: log-levels of density, wage earnings, racial diversity, income diversity, age diversity, and establishments (the outcomes we examine in Table VIII). These controls increase the R-squared and, as expected, increase the precision of our estimates relative to the baseline estimate from Table IV. The estimated effects are attenuated slightly, which is to be expected if *implicit land taxes* persist over decades and pre-2000 land taxes led to stronger year-2000 economic outcomes.

Controlling for land use regulations In columns 4 and 5 of Table V, we include controls for land use regulation and land supply elasticity. These controls account for potential differential growth trajectories depending on a county's land supply elasticity and land use regulations. Here, we control for these determinants of growth using data on county-level land supply elasticities from Saiz (2010) and the Wharton Index of Land Use Regulation from Gyourko et al. (2008). The downside of controlling for these variables is that they are available for a small subset of counties. Despite the sample limitations, we find estimates sufficiently precise to be statistically greater than zero.

Controlling for tax assessor characteristics In column 6 of Table V, we include a control for whether the tax assessor uses a computer-assisted mass appraisal (CAMA) system. These models can be used within a valuation or cost model based on the property's characteristics. These models save time and money and provide a systematic approach to tax assessments. We control for their use in case our model of the tax assessment process is a better (or worse) fit when the tax assessor uses these systems. The estimate remains large and statistically significant with this control.

Using a different hedonic model In columns 7 and 8 of Table V, we use a different hedonic model to calculate the *implicit land tax*. Specifically, this hedonic model includes ZIP code fixed effects (λ_n and ϕ_n in equations 2 and 3) to absorb neighborhood-specific

TABLE V

ROBUSTNESS

	Dependent variable: Density Growth, 2000-2020							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implicit Land Tax	1.977***	1.551***	1.202***	1.672***	1.455**	1.911***	1.764***	1.132***
	(0.699)	(0.365)	(0.357)	(0.585)	(0.679)	(0.393)	(0.421)	(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 between 2000 and 2020 on the *implicit land tax* (computed using the sales-only sample). Columns 3 and 5 include year-2000 controls: (log of) population density, population-weighted density, labor earnings, establishments, and diversity. Bootstrapped standard errors clustered at the state level are reported in parentheses. In columns 7 and 8, the *implicit land tax* is computed with ZIP code fixed effects. Other columns include controls for tax assessor characteristics, land use regulation, and/or land supply elasticity. *, **, and *** indicate significance at the 0.1, 0.05, and 0.001 levels.

amenities. The estimated effects with this alternative measure of the *implicit land tax* are similar to the estimates from the baseline measure. The estimated effect of the *implicit land tax* remains statistically greater than zero. In appendix C, we provide additional estimates from 30 additional hedonic models for a subset of the data. The *implicit land tax* is similar across these models.

Alternative timing In Table VI, we report estimates from equation (9) that use alternative timing to rule out specific types of endogeneity. By construction, the *implicit land tax* is plausibly exogenous with respect to local outcomes. Nonetheless, there may be an unknown source of endogeneity in our *implicit land tax* measure. To address this possibility, we examine the relationship between density growth and a pre-determined measure of the *implicit land tax*. Specifically, we examine the effect of the *implicit land tax* measured using pre-period data on post-period (2010–20) growth. Columns 1 and 2 show a positive and statistically significant effect of the predetermined *implicit land tax*. The magnitude of the effect is approximately half of the effect on growth over the full 2000–2020 period (columns 3 and 4), which suggests that the effect of the *implicit land tax* is proportional to the growth horizon.

The predetermined *implicit land tax* measure is advantageous for removing a potential source of endogeneity. To assess the effect of the *implicit land tax* that corresponds to the growth period, in columns 5 through 8, we regress density growth on the post-period *implicit land tax*. To remove the influence of endogeneity from growth to the *implicit land tax*, we instrument for the post-period *implicit land tax* with the predetermined pre-period *implicit land tax*. Our IV estimates indicate a strong effect of the *implicit land tax* on density growth, with (slightly) higher precision of the estimates in the subsample of counties with precise estimates of the *implicit land tax* (columns 7 and 8).

TABLE VI

ALTERNATIVE TIME PERIODS AND IV ESTIMATES

	Full Sample						Precise Subsample	
	OLS				IV			
Population Density Growth Period	2010-2020		2000-2020		2010-2020			
	(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

This table reports coefficients from county-level regressions of growth in population density on the *implicit land tax* computed using pre-period data (columns 1 through 4) or using the post-period data (columns 5 through 8). In the latter columns, the pre-period *implicit land tax* is an instrument for the post-period *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.

TABLE VII

PLACEBO TESTS

	Density Growth, 2000–2010					
	Full Sample			Unstable Subsample		
	(1)	(2)	(3)	(4)	(5)	(6)
Implicit Land Tax (Post Sample)	0.224	0.367	0.233	0.096	0.220	0.188
	(0.562)	(0.308)	(0.259)	(0.554)	(0.341)	(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 grown 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 In Table VII, we report placebo test estimates to investigate unobserved factors. One potential concern with a causal interpretation of our estimates is that an unobserved factor could affect both the *implicit land tax* and economic growth. To address this possibility, we run placebo regressions of the pre-period (2000–2010) density growth on the *implicit land tax*, measured using the post-period data. If an unobserved factor is driving both post-2000 growth and influencing our measure of the *implicit land tax*, we should observe a strong positive estimate in these placebo regressions. Of course, the existence of a positive estimate does not necessarily indicate the influence of non-tax factors; the persistent land taxes that prevailed before 2000 (and into the 2000s) could influence 2000–2010 growth and—due to persistence in land taxes—be correlated with the post-period *implicit land tax*. To limit the possible influence of persistent *implicit land taxes*, we also limit the sample to counties for which the *implicit land tax* changed considerably from the pre-period to the post-period. Specifically, we limit the sample to the counties that were *excluded* from the set of stable counties in the regressions in columns 3 and 4 from Table IV.

The estimated relationship between pre-period density growth and the post-period *implicit land tax* is indistinguishable from zero across specifications. The point estimates are especially close to zero for the unstable subsample, limiting the potential that unobserved factors explain our main effects.

4.3. *Implicit land tax effects on Population-Weighted Density, Diversity, Entrepreneurship, and Earnings*

Our baseline results document that *implicit land taxes* are associated with higher population density. Here, we examine the effect of the *implicit land tax* on population-weighted density. As pointed out by Brueckner and Kim (2003), the desirability of changes in property taxes hinges on their implications for the distribution of the population *within* counties or cities. The population-weighted density measure provides evidence on whether the increase in county-wide density we find is associated primarily with a higher concentration of the population within the county's population centers or with a dispersion of the (higher) population across the county. We also examine various other economic outcomes, including total wage earnings, neighborhood diversity, and small business formation (measured by the number of establishments).

TABLE VIII

LAND TAXES AND ECONOMIC OUTCOMES

Growth in:	Population-weighted density (1)	Wage earnings (2)	Racial diversity (change) (3)	Income diversity (change) (4)	Age diversity (change) (5)	Establishments (6)
Panel A: OLS (full sample, growth from 2000-2020)						
Implicit Land Tax	1.235***	1.932***	0.609***	1.140***	0.355*	2.073***
	(0.526)	(0.599)	(0.209)	(0.237)	(0.187)	(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
Panel B: IV estimates (precise subsample, 2010-2020)						
Implicit Land Tax	6.207***	5.979**	3.349***	2.854***	0.050	6.913***
	(2.256)	(2.940)	(1.128)	(1.075)	(0.304)	(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.

We report in Table VIII that counties with higher *implicit land taxes* have strong increases in most of our economic outcomes. The strong effect of the *implicit land tax* on population-weighted density reported in column 1 indicates a greater concentration of the population rather than a dispersion of the population across the county. Consistent with the increase in population density, we also observe an increase in overall labor market earnings (column 2). Although more concentrated populations do not need to be more diverse, we also find that the *implicit land tax* is associated with an increase in racial diversity (column 3), income diversity (column 4), and age diversity (column 5).

The effect on diversity is especially notable in light of federal programs, such as the Low Income Housing Tax Credit (LIHTC), that aim to increase income diversity. McGuire and Seegert (2022) find that, despite this goal, the Low Income Housing Tax Credit decreases rather than increases income diversity in neighborhoods where developments received tax credits. In this context, it is interesting that we find that *implicit land taxes* positively affect diversity. Specifically, a one-percentage-point increase in the *implicit land tax* is associated with a 0.609% increase in racial diversity, measured as entropy according to equation (7) (column 3). One potential mechanism is that land taxes induce redevelopment, which lowers the barrier to new residents moving in and increases mixing.[9]

Finally, we document in column 6 of Table VIII a large increase in business establishment formation. A percentage-point increase in the *implicit land tax* is associated with a 2.073% increase in establishment growth between 2000 and 2020. One possible explanation for this large positive effect is the substitution from home production toward market-based purchases in dense neighborhoods, as documented in Murphy (2018). If land taxes induce a larger post-tax price of land, then the theory in Murphy (2018) implies that local areas will feature more service establishments, greater residential density, and higher earnings among residents.

Panel B of Table VIII reports the IV estimates of the effect of the *implicit land tax* on these economic outcomes. The empirical specification is the same as in columns 7 and 8 in Table VI and given in equation (10): the independent variable is the post-period *implicit land tax* instrumented with the pre-period *implicit land tax*. Except for age diversity, the IV estimates indicate strong effects on economic outcomes with large magnitudes, consistent with the large IV estimates from Table VI.

5. THEORETICAL FRAMEWORK

In this section, we formalize the effects of land taxation on density and other economic outcomes in a setting in which land and buildings are combined to produce housing. This model provides insights into the mechanisms driving our empirical results; and our empirical results provide insights into the modeling assumptions that rationalize them. Given the

[9]This mechanism is consistent with recent work on the local effects of new housing in low-income areas (Asquith et al., 2021, Mast, 2023).

relatively small geographic unit (county) in our empirical analysis, we model a small open economy with an endogenous population level and an inelastic supply of land devoted to residential purposes. Other models of property taxes (e.g., Brueckner and Kim, 2003) are based in a monocentric-city setting in which the amount of land used for residential purposes is endogenous, but the population is exogenous. We instead focus on an endogenous population with full utilization of residential land, which conforms more closely to our empirical setting and more closely resembles recent models of household sorting across residential locations (e.g., Couture et al., 2021).

We begin by demonstrating conditions under which a confiscatory tax on land does not affect economic outcomes other than the land price. In short, the tax is non-distortionary such that land prices adjust to offset the higher taxes fully. If the tax revenue is rebated back to residents (rather than being confiscated), then the tax leads to higher after-tax real incomes for residents, which induces an inflow of new residents. We then demonstrate that for plausible model parameterizations, a structure tax raises local living costs and induces population outflow.

After evaluating the separate effects of land taxes and structure taxes, we consider the effect of reallocating the tax burden from structures to land, holding fixed total tax revenues. The model predicts positive effects on population and housing per resident (consistent with our baseline estimates). The exception to this prediction is that if local residents fully own the land, the decline in land prices reduces net income, preventing a population inflow. Housing per capita nonetheless increases due to the reduction in the structures tax.

Finally, we extend the model to evaluate the effects of a land tax on the concentration or dispersion of the population across neighborhoods within the county. Specifically, we consider a county with two locations—a downtown characterized by an inelastic supply of land and a suburb characterized by a price-elastic supply of land. In this setting, a county-wide land tax leads to a higher concentration of the population in the downtown location. This is because land prices fall more downtown (due to inelastic land supply) than in the suburbs, which lowers the relative cost of living downtown. Therefore, a land tax increases population-weighted density, consistent with our empirical evidence.

The conclusion that emerges is that *implicit land taxes* lead to increases in real incomes that induce a population inflow, which corresponds with increasing density and other economic outcomes that we observe empirically. Under a wide range of parameter values, the tax burden reallocation also causes land prices to fall. However, under parameter values that lead to the strongest growth effects of the tax reallocation, land prices can increase. In particular, a high elasticity of substitution between land and structures leads to large density effects. In this case, the cost-of-living index is very sensitive to structure tax reductions, as people substitute land for cheaper structures. The increase in population inflow from the land tax puts upward pressure on land prices, which can be large enough to offset the decrease in land prices from the direct effect of land taxes. Guided by this insight, we conclude this section by empirically evaluating the conditions under which the *implicit land tax* leads to the strongest population responses.

The theoretical exercise assumes that prices fully adjust to the land tax such that land markets clear. In policy debates, this full capitalization from land taxes to lower land values is often considered a limitation on the effectiveness of the land tax. In our model, land taxes nonetheless have strong effects because of the benefits of tax revenue. For simplicity, we abstract from various frictions that could limit capitalization of land taxes into land prices along the transition to the new steady-state. As emphasized by proponents of a land tax, such frictions further stimulate density and development by limiting the option value of holding undeveloped land. In that sense, our theoretical framework should be considered a conservative mapping from land taxes to density.

5.1. *Model*

Consider a neighborhood with a fixed quantity of land L and an endogenous population of households indexed by j. Conditional on living in the county, households have utility over housing H and other imported goods C,

$$U_j = H_j^{\alpha} C_j^{1-\alpha}. \tag{11}$$

Housing is comprised of land and structures S:

$$H_j = \left(\psi L_j^{\frac{\gamma-1}{\gamma}} + (1-\psi) S_j^{\frac{\gamma-1}{\gamma}}\right)^{\frac{\gamma}{\gamma-1}}, \tag{12}$$

where γ is the elasticity of substitution between land and structures. We assume $\gamma < 1$ to reflect complementarity between the housing inputs (which is consistent with the estimates in Albouy and Ehrlich, 2018).

Households maximize their utility given in equation (11) subject to their budget constraint. Households have exogenous labor income I_j. The per-unit price of land is r; households pay $rL_j(1+\tau_L)$, and τ_L is the tax on land. Households may also receive land rental income $\xi r\overline{L}$, where $\overline{L}$ is the average land consumption in the county and $\xi \in [0,1]$ parameterizes the extent to which local residents own land. The exogenous price of imported material for structures is p_S, such that households pay $p_S S_j(1+\tau_S)$ for their structures consumption, and τ_S is the tax on structures.[10] Tax revenues on land and structures are given by $T_j \equiv rL\tau_L + p_S S\tau_S$, where $S = \sum_j S_j$ and $L = \sum_j L_j$. These taxes may be confiscated or rebated to households, such that households receive $\kappa\overline{T}$, where $\overline{T}$ is the average tax revenue in the county, and $\kappa \in [0,1]$ parameterizes the extent to which households benefit from the tax revenues. Finally, C is the numeraire. Together, the budget constraint is,

$$I_j + \xi r\overline{L} + \kappa\overline{T} = rL_j(1+\tau_L) + p_S S_j(1+\tau_S) + C_j. \tag{13}$$

Note that if absentee landlords own all land, then ξ=0, and if residents receive no benefit from tax revenues, then $\kappa = 0$.

We use a reduced-form representation of neighborhood demand that arises from a discrete-choice model with heterogeneous preferences over locations (e.g., Couture et al., 2021) or representative-agent models with CES preferences over locations (e.g., Murphy, 2024). Neighborhood demand depends on the consumer price index $P \equiv \frac{1}{(1-\alpha)\alpha} p_H^{\alpha}$, where $p_H \equiv (\psi(r(1+\tau_L))^{1-\gamma} + (1-\psi)(p_S(1+\tau_S))^{1-\gamma})^{\frac{1}{1-\gamma}}$ is the price of housing and ϵ is the elasticity of neighborhood demand with respect to real net income. Specifically, the number of households N that live in the neighborhood is an increasing function of the real (net) income associated with living there:

$$N = \left(\frac{I + \xi r\overline{L} + \kappa\overline{T}}{P}\right)^{\epsilon}. \tag{14}$$

Production We assume that all markets are competitive. For ease of exposition, we model households as purchasing land and structures to produce housing, although an equiv-

[10] In this setting, a property tax τ that reflects market values of land and structures would be an equivalent tax on land and structures. More precisely, it would be $\tau = \tau_L = \tau_S$.

alent approach would be to explicitly model perfectly competitive housing developers that purchase inputs and sell final housing developments to households.

Equilibrium An equilibrium consists of land prices r, land per resident L_j, structures per resident S_j, and the number of residents N. Residents maximize utility subject to their budget constraints (and the exogenous structures prices and consumption prices therein), the number of residents is given by equation (14), and the land market clears:

$$NL_j = L. \tag{15}$$

Residents do not take into account the effect of their decisions on tax remittances $\overline{T}$ or income from owning land $\xi r \overline{L}$, which implies that the first-order condition between land and structures is

$$\frac{S_j}{L_j} = \left(\frac{1-\psi}{\psi}\frac{r(1+\tau_L)}{p_S(1+\tau_S)}\right)^{\gamma}. \tag{16}$$

The four equations—(13), (14), (15), and (16)—yield a system of four equations in the four endogenous variables.

We analytically derive comparative statics around an equilibrium in which land and property taxes are zero and absentee landlords own land. It is straightforward to demonstrate that the equilibrium can be characterized by an upward-sloping relationship between L_j and r (based on equations (16) and (13)) and a downward-sloping relationship between L_j and r (based on equations (14) and (15)), which guarantees uniqueness of the equilibrium. We evaluate numerical simulations under alternative parameterizations of the model.

5.2. *Effects of a Land Tax*

An increase in the land tax causes households to prefer to substitute away from land toward structures for a given land price, as demonstrated by the first-order condition shown in equation (16). However, the land market must clear, which requires the land price to fall to induce households to purchase the available land. This decline in the land price can fully or only partially offset the effect of the land tax increase. A critical factor in determining whether land prices fully or only partially offset the increase in the land tax is the extent to which tax revenues are rebated to households.

PROPOSITION 1: *If taxes are not rebated back to the household ($\kappa = 0$), then a land tax increase is fully offset by a decline in the land price, such that the equilibrium population and structures per capita do not change. In particular, $r(1+\tau_L)$ remains fixed such that*

$$dr = -\frac{r}{1+\tau_L} d\tau_L, \tag{17}$$

where dr is the total derivative of the land price, and $d\tau_L$ is the total derivative of the land tax.

PROOF: By contradiction. Substitute out S from the budget constraint (equation 13) using the first-order condition (16) to yield

$$\alpha I_j = L_j \left(r(1+\tau_L) + p_S \left(\frac{1-\psi}{\psi} \frac{r(1+\tau_L)}{p_S} \right)^{\gamma} \right), \tag{18}$$

where we impose $\kappa = 0$ and $\tau_S = 0$. The only endogenous variables in this equation are r and L_j. Suppose that $r(1+\tau_L)$ increases. Then, per equation (18), L_j must fall. And by equation (14), the number of households in the neighborhood must fall. But a decline in L_j and N would violate land market clearing. The same reasoning implies that $r(1+\tau_L)$ cannot increase. Therefore, $r(1+\tau_L)$ remains constant. *Q.E.D.*

Intuitively, changes in r must perfectly offset changes in τ_L in the households' first-order conditions to ensure a constant demand for land such that land markets clear. This result is consistent with the standard result that taxation of inelastic production factors is non-distortionary.

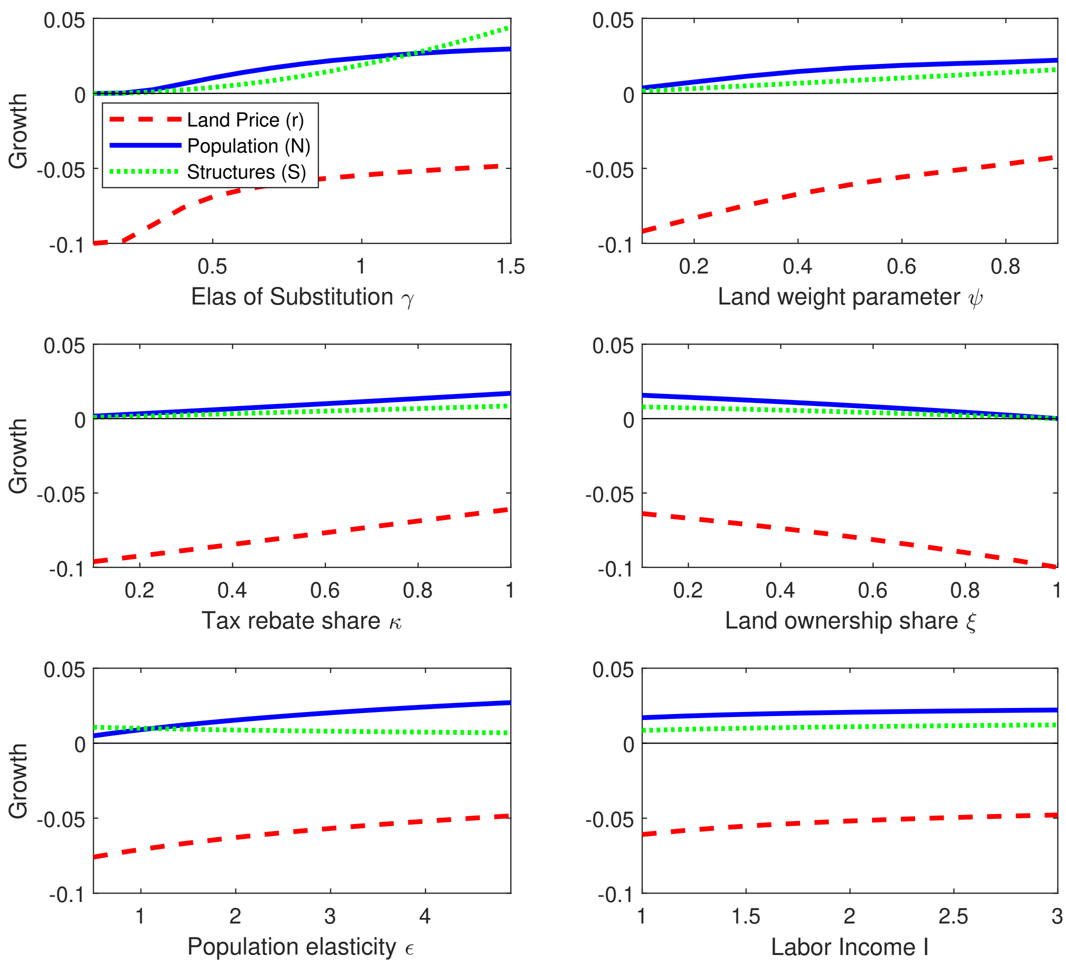
The results are quite different under the alternative (and realistic) assumption that tax revenues yield benefits to residents, which we model as a rebate back to the households ($\kappa > 0$). In particular, it can be shown that small land tax increases unambiguously lead to higher population density.

PROPOSITION 2: *If taxes are rebated to the household ($\kappa > 0$) and some land is owned by absentee landlords ($\xi < 1$), then a land tax increase leads to an inflow of residents to the neighborhood.*

The increase in tax revenues increases the net income of households (since absentee landlords bear some of the tax) relative to the $\kappa = 0$ scenario in which real net income was independent of the land tax. The increase in net income induces an inflow of households (by equation (14)). The higher net demand for land in the neighborhood increases gross-of-tax land prices. The net-of-tax land price r falls, but not by as much as it would have in the absence of the rebate.

FIGURE 5.—Effect of a land tax, sensitivity to parameter values

FIGURE 5.—Note: This figure shows the effect of a 10% increase in the land tax on growth in population, structures, and the land price under various parameter values.



The magnitude of the changes in land prices and population depends on the model's parameter values. To provide a sense of how these parameters influence the magnitude of the land tax effect, we simulate the model under various ranges of parameter values. Figure 5 plots the effects of a 10% land tax. Each subplot reports how the tax effect varies with one of the model parameters, holding the others fixed. Our baseline parameter values (around which other parameter values change) are $\gamma = 0.7$ (consistent with Albouy and Ehrlich (2018)), $\kappa = 1$ (so that all tax revenue is rebated), $\epsilon = 2.3$ (based on the population elasticity to income in Couture et al. (2021)), and $p_S = 1$. We normalize the land size to unity and set income to unity.

The land tax lowers the price of land. Higher values of the benefit of tax revenues κ and the neighborhood demand elasticity ϵ are associated with a smaller decline in the land prices, a reflection of higher demand for living in the neighborhood when taxes are rebated to residents.

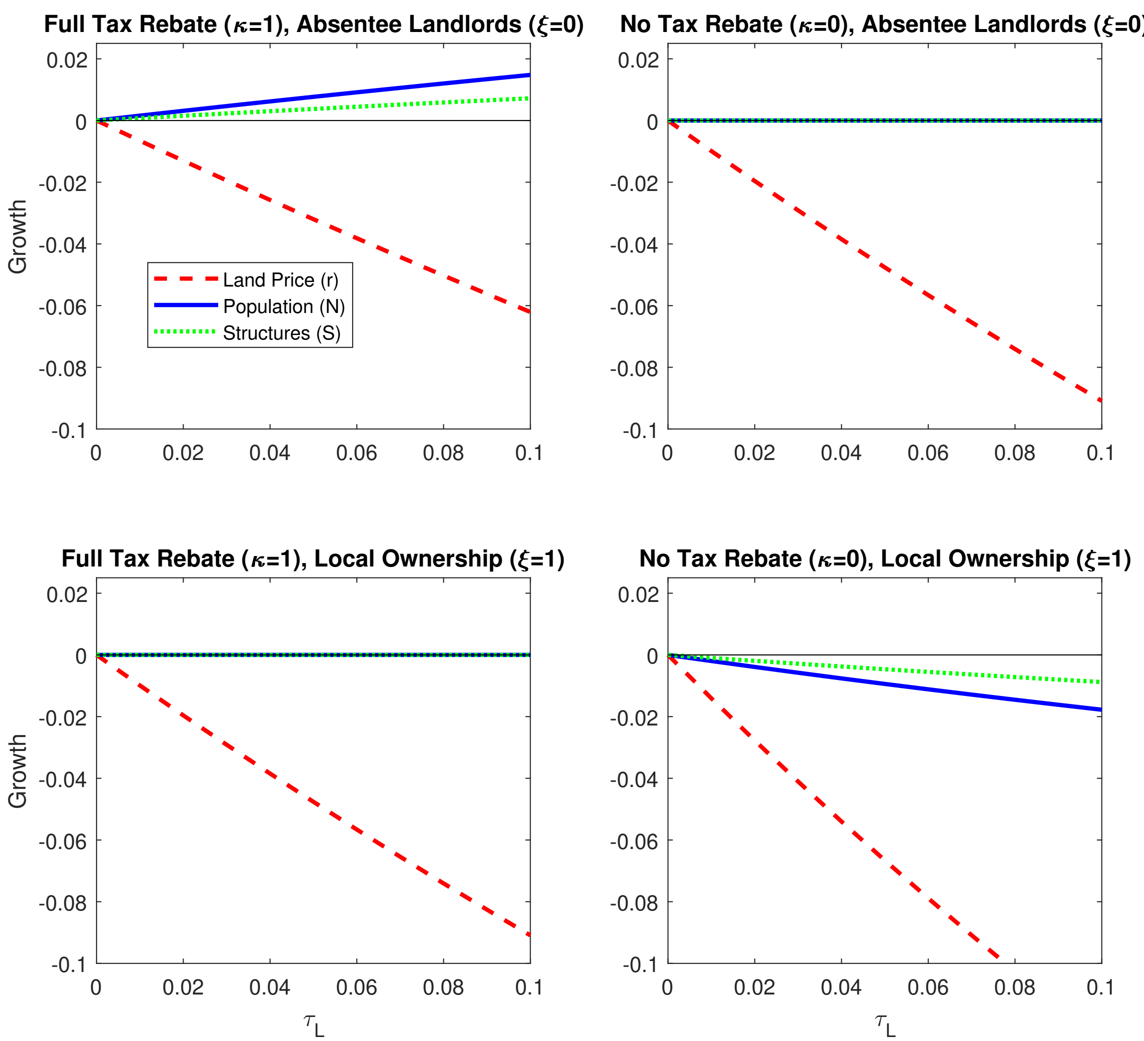
The values of rebate shares (κ) and the local land ownership share (ξ) are particularly important for determining whether land taxes can increase density. Larger rebate shares are associated with stronger population inflows, whereas a larger share of local land ownership is associated with weaker population inflows. The more local residents own land, the more their net income declines from the land tax. Figure 6 demonstrates the effect of a land tax under a combination of the extreme values (0 or 1) for κ and ξ. Land taxes positively affect population only if $\xi < 1$ and $\kappa > 0$.

5.3. *Additional model analyses*

We continue the theoretical analysis in Appendix D, which begins by demonstrating that a tax on structures raises local living costs and induces population outflow. Having established the independent effects of land taxes and structures taxes, the analysis then evaluates the effects of reallocating the tax burden from structures to land, holding fixed total tax revenues. The model predicts positive effects on population and housing per resident (under reasonable parameter values).

The effects of reallocating tax burden from structures to land are particularly strong when γ (the elasticity of substitution between land and structures) and ϵ (the population elasticity with respect to income) are high. A high elasticity of substitution between land and

FIGURE 6.—Effect of a land tax, extreme values of rebate shares and land ownership shares



structures implies that households can easily substitute toward less-expensive structures, thereby causing a larger decline in the cost of living from a reallocation of the tax burden away from structures. A high value of the population elasticity implies a strong population response to the lower cost of living induced by the tax burden reallocation. Land prices can even increase if both elasticities are high. In such cases, the structures tax decrease implied by constant revenues is much stronger than the increase in the land tax; the cost-of-living decline and resulting population influx are so large that land prices must increase to clear the land market.

We find empirical support for these model predictions. We conjecture that population elasticities are higher over longer time horizons and that households are more likely to substitute structures for land in dense areas. We also conjecture that the positive effects of implicit land taxes are more likely to manifest in counties with relatively relaxed regulations on housing development. We find empirical support for these conjectures, reported in the appendix. As further external validation of the model, we also evaluate the effects of the *implicit land tax* on land values. Consistent with the theory, land price responses are more positive (and/or less negative) in counties with higher initial-period density.

We also consider the effects of a land tax on the concentration or dispersion of the population across neighborhoods within the county. Specifically, in Appendix D.4, we consider a county with two locations—a downtown characterized by an inelastic supply of land and a suburb characterized by a price-elastic supply of land. This extension serves two purposes. First, it helps formalize our empirical evidence that land taxes induce the concentration of the population within counties. Second, it allows us to examine the effect of a land tax that is imposed on both locations, which is indicative of the effects of a national land tax. In other words, the model extension offers a guide to the sorting effects of a land tax imposed across the *country*; the downtown represents large cities with inelastic housing supply, and the suburb represents all other areas with larger housing supply elasticities. If we were to impose a tax only on the downtown location, then this model extension would be similar to the baseline single-location model above but with an explicit derivation for demand for living downtown (rather than the reduced-form population demand equation given in equation (14)). In this setting, a county-wide land tax leads to a higher concentration of the population in the downtown location. This is because land prices fall more downtown (due to inelastic land supply) than in the suburbs, which lowers the relative cost of living downtown. Therefore, a land tax increases population-weighted density, consistent with our empirical evidence.

6. CONCLUSION

Explicit land taxes are rarely implemented despite their desirable theoretical properties. This lack of implementation may reflect the circular reasoning that, without evidence of the effects of land taxes, urban planners are reluctant to implement them. Yet, in the absence of broad implementation, evidence of their effects remains lacking.

In this paper, we have proposed an alternative approach to estimating the effects of land taxes by deriving a measure of *implicit land taxes*. Specifically, we measure land taxes based on idiosyncratic deviations in how assessors tax land relative to the implicit market value of the land.

We document several facts about land taxes. First, *implicit land taxes* vary substantially across U.S. counties: the 10th and 90th percentile of *implicit land tax* are -1.9% and 0.6%. This tax rate dispersion is large compared to the 10th and 90th percentile of the effective property tax rates of less than 0.001% and 0.9%. Second, *implicit land taxes* are spatially dispersed. There is considerable variation in our measure of *implicit land taxes* across the country and within metropolitan statistical areas. Third, *implicit land taxes* are associated with higher growth in a range of economic outcomes. *Implicit land taxes* are associated with population and earnings growth, an increase in the concentration of the population within counties, growth in racial, income, and age diversity, and an increase in business formation.

To interpret this evidence, we present a model of land taxes. In the model, land taxes have neutral effects when they are confiscated but positive effects on density and population-weighted density when tax revenues are used for purposes that benefit local residents. Taxes on structures increase local costs of living and lead to declines in population density. A reallocation of the tax burden from structures to land has large economic benefits. Based on the theoretical importance of the elasticity of substitution between land and structures, these benefits are likely to be particularly strong over long time horizons and in dense areas.

Our theory predicts that land taxes can have large effects even if land values fully capitalize the higher land tax. The theoretical benefits of the land tax are likely to be even stronger in the presence of frictions that prevent full capitalization. Exploring the role of such frictions is an important topic for future work. Other avenues for future work include exploring the effect of land taxes in areas zoned for non-residential use and investigations of incidence across income, age, and geography.

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ONLINE APPENDICES

APPENDIX A: DATA CONSTRUCTION

We combine several data sets to estimate the effect of the *implicit land tax* on density and other economic outcomes. To estimate the *implicit land tax*, we use parcel-level, administrative assessor data on tax and property characteristics from ATTOM Data Solutions from 2006 to 2016 for the continental U.S. These data include 374 million parcels from more than 2,750 of the 3,243 US counties or county-equivalents. We validate these data using parcel-level data from ZTRAX. We link these data sources using parcel numbers assigned by the local tax assessor and ZIP code. We expand this link using parcel numbers and street addresses, and then street addresses and ZIP codes following Bradley et al. (2023).

These data include property taxes paid, sales price, tax-assessed value, and property characteristics. We interpolate characteristic data where it is missing first by using data for the same property in other years and then by cross-checking with the ZTRAX data. We exclude purchase prices of less than $1,000 or more than $5 million. We include as many counties as possible, with the caveat that price information is lacking or of poor quality in states that have non-disclosure rules (specifically, ID, KS, LA, MS, MT, NM, ND, TX, UT, WY, and all but 4 counties in MO).

We collect several other data sources to construct our economic outcomes and control variables. We use total labor earnings from the Quarterly Census of Employment and Wages. We collect data on business establishment formation from the County Business Patterns data. We construct population density and neighborhood diversity (racial, income, and age) from Census data at the county level. We follow White (1986) in constructing entropy-based measures of diversity. This measure has been used in Heath et al. (2023) and others. We hand-collect data on tax assessors by going to each county's website. We collect data on whether the tax assessor is elected or appointed and whether they use a computer-assisted mass appraisal model.

For external validation, we collect data from Davis et al. (2021), the Wharton land use regulation index from Gyourko et al. (2008), and land supply elasticities from Saiz (2010). We use this data for controls and to cross-check our model estimates for land use.

APPENDIX B: MARKET VALUE IMPUTATION

Our estimation of the *implicit land tax* requires data on tax-assessed home values and market values. We observe the tax-assessed home values in the Zillow and ATTOM data. The market value is mainly unobserved. We observe the sales price in the Zillow and ATTOM data for a subset of properties that sell. Our baseline estimates use this sales price as the market value. This measure advantageously comes with little error—it is the price paid in the market. This measure disadvantageously limits the sample to homes in the year they sell. To quantify the magnitude of this disadvantage, we produce estimates using an imputation method that dramatically increases the proportion of homes in the data.

We impute market values in two ways. For properties with a sale in our sample, we use the sales price and the Federal Housing Finance Agency's (FHFA) annual ZIP code–level indices to impute the market value in the years without a sale. For properties with multiple sales, we do the same imputation and average the values for the years without a sale. For properties that do not have a sale in our sample and have data on characteristics, we use a hedonic machine learning imputation following Bradley et al. (2023). For properties without a sale and without data on characteristics, we cannot impute a market value.

The idea behind the market value imputation based on characteristics is to take properties with sales and estimate the relationship between the characteristics and price. With those parameter estimates, we can then impute market values for properties with those characteristics but without sales.

We account for differences in the imputation by region. Specifically, we allow the characteristics and the relationship between those characteristics and market value to differ. For example, the indicator variable for having a pool will be an important characteristic in some locations but not in others. Even for those locations that include the indicator for having a pool as a characteristic, its relationship with price may differ substantially.

We construct a two-step, inner- and outer-loop process to select the characteristics and the geographic region to estimate the parameters. Each of these choices comes with a tradeoff. The selection of characteristics has the classic tradeoff between fit and over-fitting. To account for this, we use 90% of the data for training and 10% for validation and employ an ensemble method with a histogram-based, gradient-boosting regression tree. One advantage of this method is that it accounts for non-linear relations and interactions. Another advantage is that it natively handles missing values and categorical values—both of which are important features of the data.

We regulate outliers by restricting the output from the gradient-boosting regression tree. We allow properties to vary in market value within a 10% range of the previous year's market value. If the predicted value is outside of this range, we censor the prediction—a rare occurrence in practice. Finally, with these estimates, we use the validation set to estimate the mean-squared error and choose the parameters that minimize it. This is the inner loop.

In the outer loop, we select the geographic region to estimate the model's parameters. The choice of geographic region entails the classic tradeoff between variance and bias. The larger the region used to estimate the model, the more precise the estimates. However, the larger the region used to estimate the model, the more biased it is, to the extent that properties further away have different market valuation models. To account for this, we construct an iterative model that adds Census tracts until the mean-squared error increases in subsequent estimates or until there are more than 20,000 transactions. We start with all properties in a given (focal) Census tract and append all properties in the adjacent Census tract with the minimal distance in centroids. We then produce estimates using the inner loop described above and record the mean-squared error. Next, we add the next adjacent Census tract in terms of distance between centroids. Finally, we pick the iteration that yields the lowest mean-squared error. In practice, this yields a geographic region with between 5,000 and 10,000 sales.

We apply this method to all Census tracts in our sample. The resulting imputation is, therefore, parameter- and sample-optimized at a Census-tract level.

APPENDIX C: HEDONIC MODEL

Our estimation of the *implicit land tax* depends on the estimation of a hedonic model that predicts tax-assessed values and a hedonic model that predicts market values as a function of housing characteristics. We run these models separately for each county. Our baseline models use land square footage, structure square footage, number of bedrooms, and number of bathrooms. These variables are chosen based on a LASSO selection model, which considers data availability. Our hedonic specification is otherwise a standard with foundations in Waugh (1929) and Rosen (1974). We then estimate differences in how the tax assessor and the market values land.

We find our ILT estimates are robust to different hedonic specifications. Specifically, we further test the robustness of our hedonic specifications following advice from McMillen and Thorsnes (2003), Kuminoff et al. (2010), McMillen and Redfearn (2010), and Bishop et al. (2020). In Table V, we show that our estimates of the relationship between density growth and the *implicit land tax* are robust when the hedonic specification includes ZIP code fixed effects and using different periods to test for time consistency.

Here we also test for the sensitivity of our estimates using different hedonic specifications based on data from Atlanta, Georgia. We focus on Atlanta because it is the metropolitan area with the most counties where we can estimate a *implicit land tax.* This setting provides a laboratory to explore how different hedonic specifications could affect our estimates. These tests use the 33 structure variables, the square footage of land, and their interactions. These variables include attic square footage, architecture code, finished basement, basement square footage unfinished, central air, exterior type, indicator for a fireplace, foundation type, garage square footage, garage type, heat type, number of bathrooms, number of one-quarter bathrooms, number of half bathrooms, number of three-quarter bathrooms, number of full bathrooms, number of bedrooms, number of stories, number of units, patio and porch type, privacy type, square footage of the structure, structure type, year built, effective year built, number of car garage, number of structures, construction quality, structure condition, roof type, number of fireplaces, an indicator for a pool, and year of remodeling. We also consider the interactions among these variables.

First, we consider a broad set of 30 different hedonic specifications, and we show that the standard deviation of the *implicit land tax* is greater across counties within Atlanta than across hedonic models within counties in Atlanta. Second, we show a high correlation between our baseline specification and alternative specifications. These various model specifications include interactions with different structure variables, variable selection based on LASSO for each county individually, and variable selection based on subsets of counties within the Atlanta metropolitan area. Together, these pieces of evidence indicate that our estimates are robust to alternative model specifications.

Additional hedonic model specifications. First, we consider specifications that use a LASSO procedure with different tuning parameters and the complete set of interactions and potential variables: attic square footage, architecture code, finished basement, basement square footage unfinished, central air, exterior type, indicator for a fireplace, foundation type, garage square footage, garage type, heat type, number of bathrooms, number of one-quarter bathrooms, number of half bathrooms, number of three-quarter bathrooms, number of full bathrooms, number of bedrooms, number of stories, number of units, patio and porch type, privacy type, square footage of the structure, structure type, year built, effective year built, number of car garage, number of structures, construction quality, structure condition, roof type, number of fireplaces, an indicator for a pool, and year of remodeling. In nine of the ten LASSO procedures we tried, the selected variables were some combination of our baseline structure variables without interactions. The remaining LASSO procedure chose interactions among structure characteristics. The full set of selected variables in this procedure is in the model below,

$$\begin{aligned}
A_{i,c} = {} & \beta_0 + \beta_1 \text{Lot Size} \\
& + \beta_2 \text{Number of Fireplaces} \times \text{Pool} \\
& + \beta_3 \text{Number of Units} \times \text{Effective Year Built} \\
& + \beta_4 \text{Number of Units} \times \text{Year Built} \\
& + \beta_5 \text{Number of Stories} \times \text{Number of Fireplaces} \\
& + \beta_6 \text{Number of Bedrooms} \times \text{Number of Stories} \\
& + \beta_7 \text{Number of Bathrooms} \times \text{Square Feet} \\
& + \beta_8 \text{Number of Bathrooms} \times \text{Number of Stories}
\end{aligned}$$

$$+\beta_9\text{AC} \times \text{Number of Bedrooms}$$
$$+\beta_{10}\text{Sqft unfinished in the Basement} \times \text{Square Feet}$$
$$+\beta_{11}\text{Square feet finished in the Basement} \times \text{Number of Stories}$$
$$+\beta_{12}\text{Square feet in the Attic} \times \text{Pool}$$
$$+\beta_{13}\text{Square feet in the Attic} \times \text{Number of Stories} + \varepsilon_{i,c}.$$

Next, for each LASSO procedure, we consider different combinations of our baseline variables, and we vary whether we estimate a single coefficient across all counties or allow the coefficient to differ by county. In our baseline estimates, we estimate a separate coefficient for each county-variable pair. These variations create another 14 models.

Finally, we consider variations with the five additional variables: number of car garages, an indicator for having a swimming pool, number of stories, year built, and number of fireplaces. We consider five additional models where we add each of these variables to our baseline model,

$$\begin{aligned}
A_{i,c} &= \beta_0 + \beta_1\text{Lot Size} + \beta_2\text{Number of Bedrooms} + \beta_3\text{Number of Bathrooms} \\
&\quad + \beta_4\text{Square Feet} + \beta_5\text{Additional Variable} + \varepsilon_{i,c} \\
M_{i,c} &= \delta_0 + \delta_1\text{Lot Size} + \delta_2\text{Number of Bedrooms} + \delta_3\text{Number of Bathrooms} \\
&\quad + \delta_4\text{Square Feet} + \delta_5\text{Additional Variable} + \nu_{i,c}.
\end{aligned}$$

We consider an additional five specifications, with each variable as the sole structure variable,

$$\begin{aligned}
A_{i,c} &= \beta_0 + \beta_1\text{Lot Size} + \beta_2\text{Additional Variable} + \varepsilon_{i,c} \\
M_{i,c} &= \delta_0 + \delta_1\text{Lot Size} + \delta_2\text{Additional Variable} + \nu_{i,c}.
\end{aligned}$$

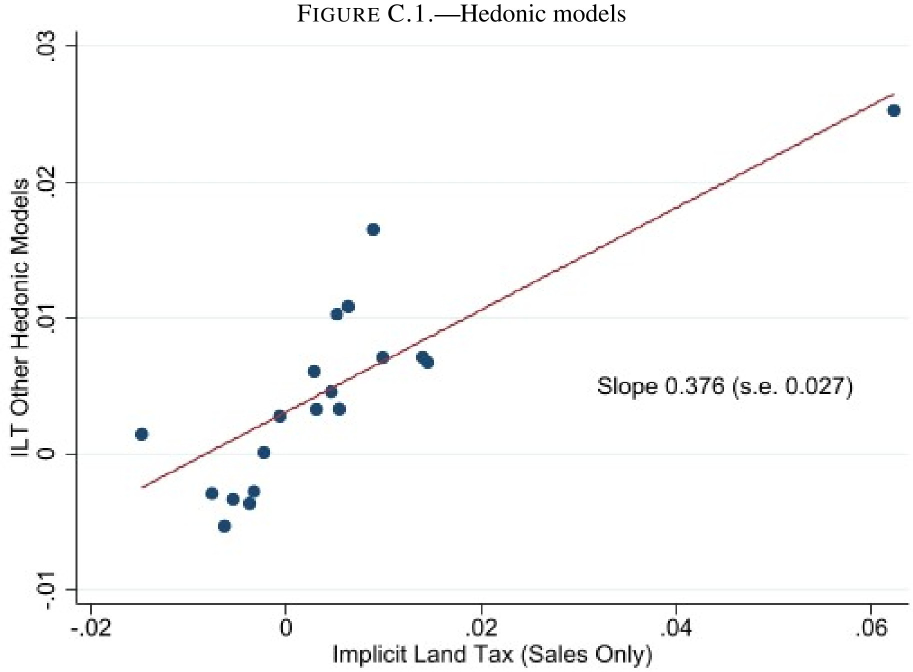
Finally, we consider five specifications with the additional variable and square feet as the structure variables,

$$A_{i,c} = \beta_0 + \beta_1 \text{Lot Size} + \beta_2 \text{Square Feet} + \beta_3 \text{Additional Variable} + \varepsilon_{i,c}$$

$$M_{i,c} = \delta_0 + \delta_1 \text{Lot Size} + \delta_2 \text{Square Feet} + \delta_3 \text{Additional Variable} + \nu_{i,c}$$

The *implicit land tax* are similar across hedonic specifications. Across the 25 counties, the standard deviation of the *implicit land tax* is 0.175. The average standard deviation within counties and across the 30 hedonic model specifications is two orders of magnitude smaller at 0.0071. In Figure C.1, we provide a scatter graph, binned, of the roughly 750 estimates from alternative hedonic model specifications and the baseline *implicit land tax*. Reassuringly, a high baseline estimate predicts a higher estimate in the alternative hedonic specifications.

FIGURE C.1.—Hedonic models



APPENDIX D: ADDITIONAL THEORETICAL MODEL ANALYSES

D.1. *Effects of a Tax on Structures*

A tax on structures unambiguously increases the gross-of-tax cost of structures (since the import price of structures is independent of the local economy), which, per equation (16), implies a decline in per-capita consumption of structures. Although the effect of τ_S on S_j is straightforward, the effect on population density is not. Once again, the effect depends on whether tax revenues are rebated to residents. If revenues are confiscated rather than rebated, there is an unambiguous decrease in real net incomes (due to increased cost of living), which induces population outflow. If the tax revenues are rebated, however, the increase in net income can substantially mitigate the extent of the population decline. Appendix Figure D.1 demonstrates how the magnitude of the population response varies depending on tax rebate shares and local land ownership shares. The effect of the structure tax is relatively invariant to other parameter values (Appendix Figure D.2).

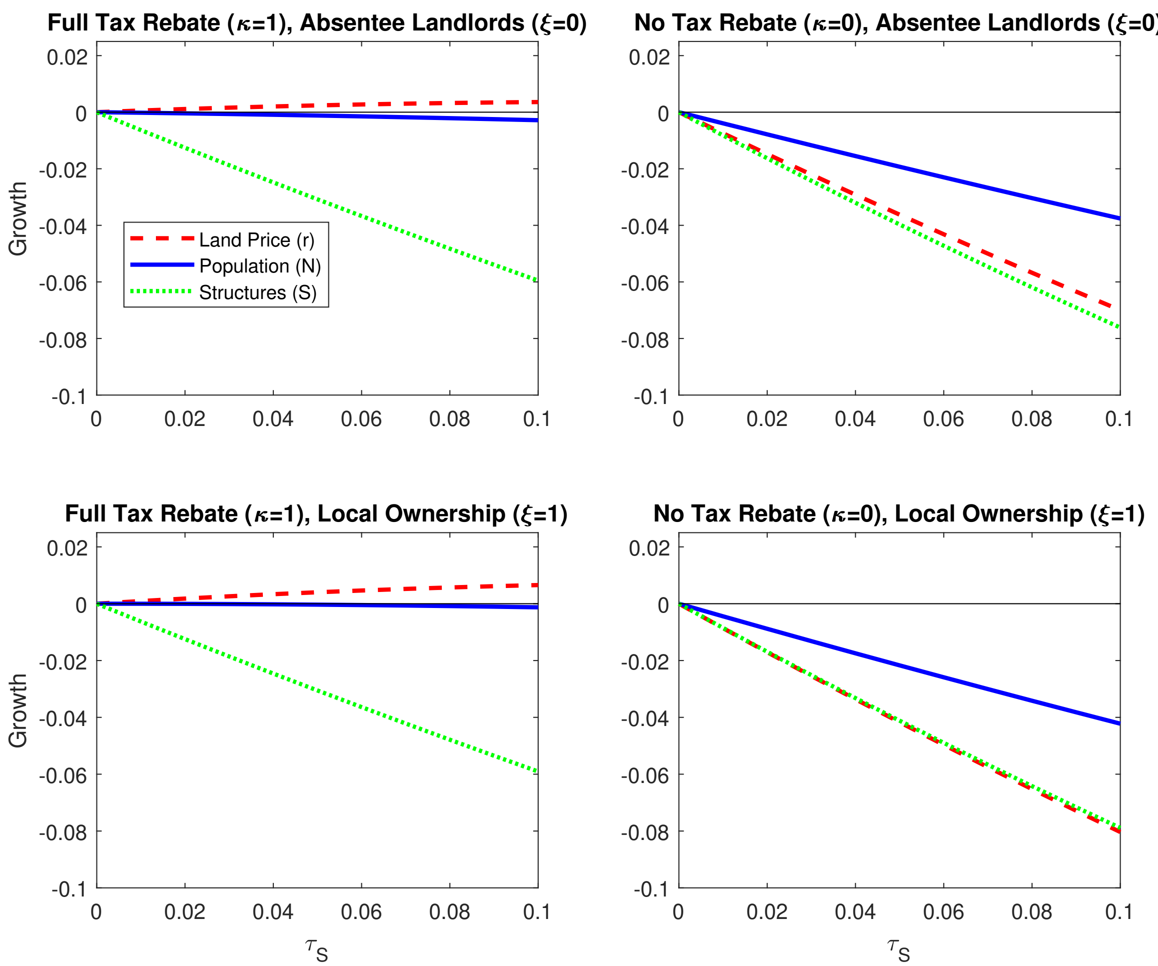
D.2. *Revenue-neutral shift of tax burden toward land*

Having established the independent effects of land taxes and structures taxes, we now examine the joint effects of an increase in the former and a decrease in the latter such that total tax revenues are held fixed.[1] To do so, we simulate the effects of an increase of 1% in the land tax (and a corresponding decrease in the structures tax to maintain constant tax revenues per capita) when per-capita property tax liabilities account for 2% of labor income.

Figure D.3 reports the effect of a simultaneous increase in land tax and a decrease in structures tax. The parameters that exert the strongest influence on the effect of this tax reallocation are γ (the elasticity of substitution between land and structures) and ϵ (the population elasticity with respect to income), so the figure focuses on variation in these parameters. The top row of Figure D.3 varies parameter values with the others held at the baseline values, while the bottom row reports the effects under larger values for ϵ (bottom-left panel) and γ (bottom-right panel). For all elasticity values, the reallocation of the tax

[1] Brueckner (1986a) also theoretically examines a revenue-neutral shift on the tax burden from land to structures. A distinguishing feature of our model is that the population is endogenous.

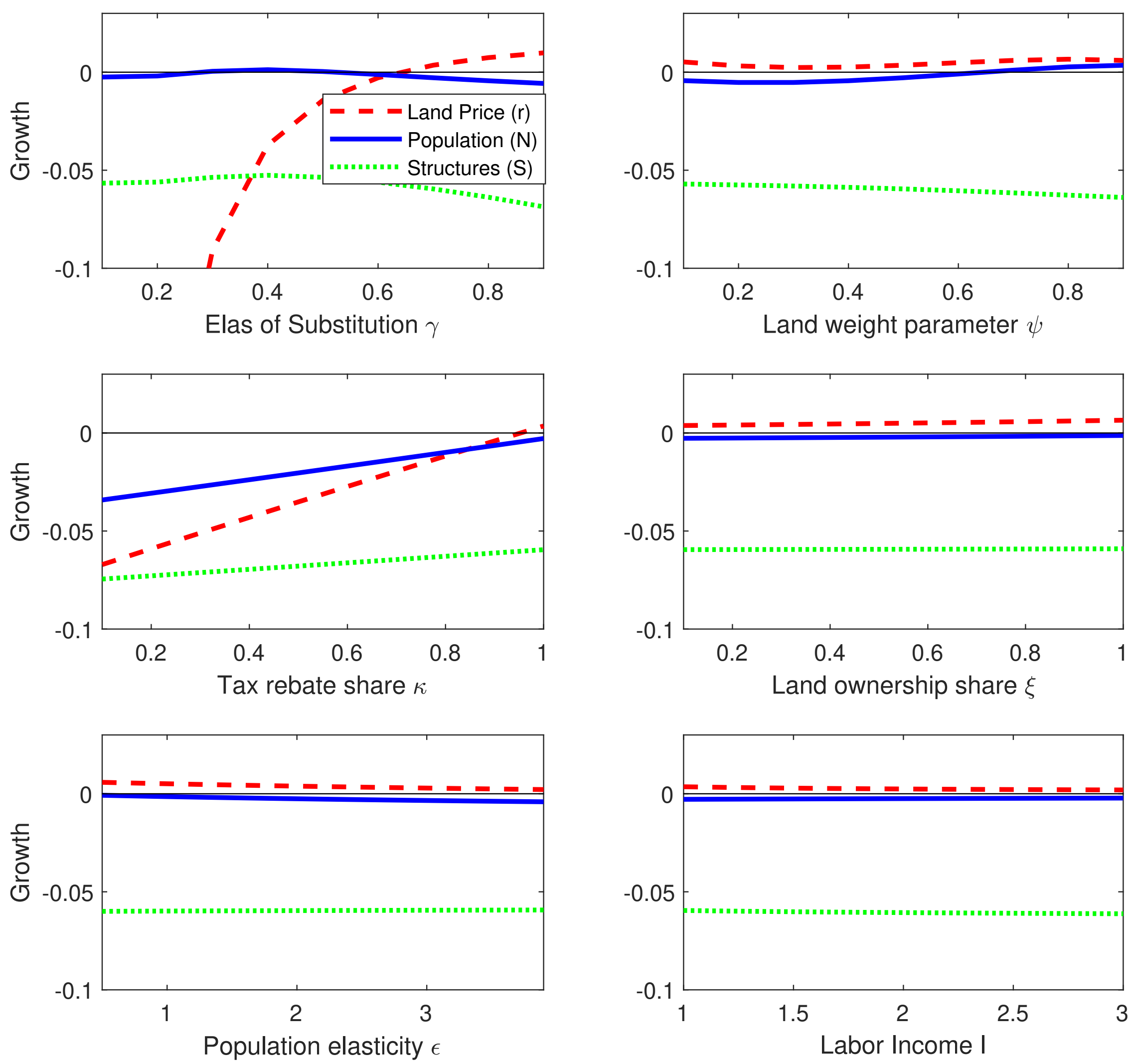
FIGURE D.1.—Effect of a structures tax, extreme values of rebate shares and land ownership shares



burden to land leads to population growth and even stronger growth in structures. In other words, housing per capita increases. The increase in structures reflects the effects of the decline in structure taxes, while the population increase primarily reflects the lower price of land induced by higher land taxes (and hence the lower after-tax cost of living). Because tax revenues are held constant, changes in rebated tax receipts drive none of these effects.

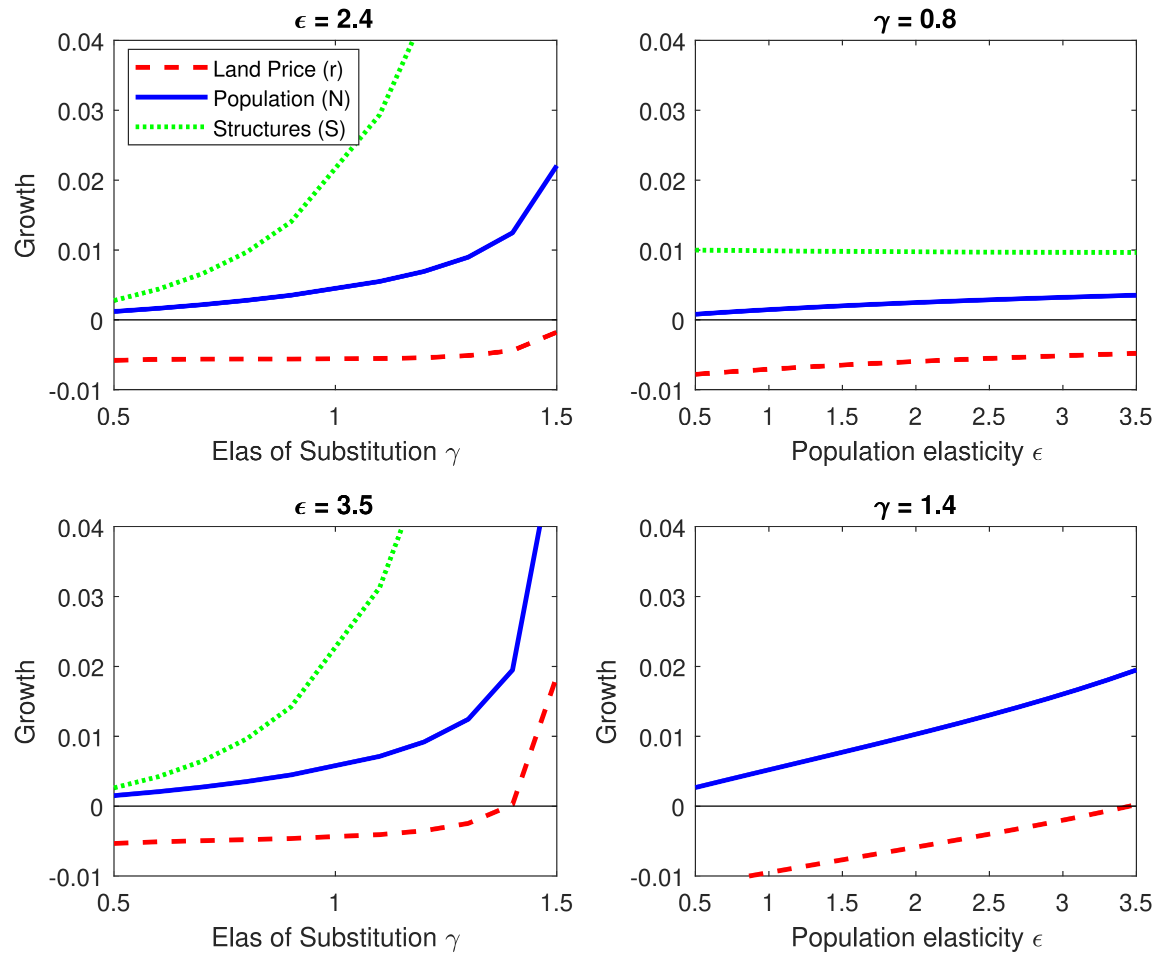
The effects of the land tax are particularly strong for high-elasticity values. A high elasticity of substitution between land and structures implies that households can easily substitute toward less-expensive structures, thereby causing a larger decline in the cost of living

FIGURE D.2.—Effect of a tax on structures, sensitivity to parameter values



from a reallocation of the tax burden away from structures. A high value of the population elasticity implies a strong population response to the lower cost of living induced by the tax burden reallocation. Land prices can even increase if both elasticities are high. In such cases, the structures tax decrease implied by constant revenues is much stronger than the

FIGURE D.3.—Effect of a revenue-neutral shift of the tax burden toward land



increase in the land tax; the cost-of-living decline and resulting population influx are so large that land prices must increase to clear the land market.

D.3. *External validation of the theory*

We have examined mechanisms driving our empirical results by first formalizing the distinct channels by which land and structure taxes affect local economic outcomes. Our empirical *implicit land tax* measure is, by construction, a reallocation of the tax burden from structures to land. Therefore, the effects of the *implicit land tax* reflect a combination of the forces operating when land taxes are increased and structure taxes are decreased. Our baseline OLS estimates imply that a 1% *implicit land tax* increases density by over 1%, which emerges from the theory under certain ranges of parameter values.

According to our theoretical assessment of a reallocation of the tax burden toward land (Section D.2 and Figure D.3), the effect of the *implicit land tax* on density is increasing in the elasticity of substitution between land and structures (γ) and increasing in the elasticity of the population response (ϵ) to local real after-tax income. The theoretical importance of each of these elasticities yields testable implications that can be used to validate the model.

First, these elasticities are likely to be higher over longer time horizons. Structures are more likely to be developed and/or changed over long horizons, and households' moving costs (e.g., information frictions or other transaction costs) are less relevant the longer the time horizon. Consistent with this intuition, our estimated effects of the *implicit land tax* are stronger over longer (two-decade) horizons. This prediction is consistent with the evidence in Table VI from Section 4.

Second, γ is likely higher in denser residential areas. For households residing in high-density Manhattan, for example, decreases in the cost of structures will likely translate into a desire for nicer housing units, perhaps in high-rises, without a corresponding increase in demand for land. Even though real incomes increase, the land footprint is unlikely to increase in Manhattan. In low-density suburbs, however, households are more likely to purchase more structures and land (and in a more equal proportion) when real income increases due to lower structure taxes.

Third, these effects are likely to manifest only in counties without strict regulations on housing development. To assess this possibility in the data, we examine whether the effects of the *implicit land tax* are stronger in higher-density areas depending on whether the county exhibits strict land use regulations. Appendix Table D.1 reports the results from regressions of density growth on and (log) density and its interaction with the *implicit land tax*,

$$\%\Delta Y_c = \alpha_S + \beta_1 \text{ILT}_c + \beta_2 \text{ILT}_c \times \log \text{density} + X_c \Gamma + e_c, \tag{19}$$

where X_c includes pre-period density. For each regression, we restrict the sample based on whether the county has strict (above median) land use regulations. To increase the precision of our estimates, we also examine specifications that restrict the sample to counties for which we have stable, precise *implicit land tax* estimates (as discussed in relation to Table IV).

Among the counties with lax land use regulations, both the direct effect of the *implicit land tax* and its interaction with density are positive and statistically significant, consistent with the intuition that structures are stronger substitutes for land in denser areas. For counties with strict land use regulations, the estimates are indistinguishable from zero.

TABLE D.1

DENSITY-DEPENDENT EFFECTS OF LAND TAXES ON POPULATION DENSITY GROWTH

	Dependent variable: density growth 2010–2020					
Land Use Regulation Value	Below Median		Above Median		Missing	
Precise Subsample	N	Y	N	Y	N	Y
	(1)	(2)	(3)	(4)	(5)	(6)
ILT	3.483*	6.626**	-1.274	-1.205	2.753*	6.998***
	(1.886)	(2.798)	(1.303)	(2.229)	(1.508)	(2.038)
ILT X (log) pop-weighted density 2010	0.387*	0.676**	-0.241	-0.299	0.208	0.597***
	(0.223)	(0.319)	(0.170)	(0.313)	(0.149)	(0.205)
State Fixed Effects and density controls	Y	Y	Y	Y	Y	Y
N	451	306	456	303	1139	833
R2	0.397	0.432	0.456	0.435	0.360	0.406

This table reports coefficients from county-level regressions of 2010–20 population density growth on the *Implicit Land Tax*, pre-period (2010) log population–weighted density, and the interaction between (log) population–weighted density and the ILT. The sample in columns 1 and 2 is limited to counties with low (below median) values of the Wharton Land Use Regulation Index. The sample in columns 3 and 4 is limited to counties with high land use regulation values. The sample in columns 5 and 6 is limited to counties with missing values for the WRLURI. The sample in columns 2, 4, and 6 is limited to counties with precise estimates of the ILT. All regressions include state fixed effects and control for log density in 2010. Standard errors, clustered at the state level, are reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.001 levels.

Effects on Land Values An additional testable prediction of our theory is that we should observe declining land values only when the *implicit land tax* exerts a mild effect (e.g., Figure D.3). Our baseline estimates of the effect of the implicit land tax are strong and above unity. Our IV estimates yield even stronger effects of the *implicit land tax*. Therefore, we do not expect to find strong negative effects of the *implicit land tax*. To test this prediction, we examine the effects of several measures of land values: (1) median home price growth, (2) changes in our estimates of marginal land values from the pre-period to the post-period, and (3) growth in land value estimates from Davis et al. (2021) over the span of their sample (2012-2019). Appendix Table D.2 reports both OLS and IV estimates of the effect of the *implicit land tax* on these land value measures. None of the specifications yields estimates statistically below zero. For the IV specifications, which are associated with the strongest density growth estimates (Table VI), all estimates of the effects on land values are positive, and some are statistically significant. Taken together, our estimates of strong growth effects alongside non-negative land value effects are consistent with the theory's predictions.[2]

Table D.3 further investigates the correspondence between land value growth and density growth by exploiting heterogeneity in counties' responses to the *implicit land tax*. We have already documented that higher initial-period density is associated with higher density growth effects of the *implicit land tax* (see the discussion above in relation to Appendix Table D.1). Our theory suggests these counties should also exhibit more positive effects on land value. Table D.3 assesses this prediction using the IV specification that yields the strongest growth estimates and for the sample for which we would expect to observe density-dependent effects: counties without strong land use restrictions. The results indicate that, within this sample, the *implicit land tax* causes stronger land value growth and density growth in counties with higher initial-period density.

Summary of Model Predictions Our theoretical setting demonstrates that the conditions required for positive economic effects of the *implicit land tax* are quite general. Even an increase in the land component of the property tax can induce increases in population density and concentration within a tax jurisdiction. A corresponding reduction in the tax on structures reduces local housing costs and amplifies this effect.

Even though the *implicit land tax* has strong average effects, its benefits need not be evenly distributed. Landowners are less likely to benefit if land values fall due to the higher land tax. However, land prices can increase when households are willing to substitute struc-

[2]Our model implies that land prices fully adjust so that land markets clear. As discussed above, the effects would be even stronger if land prices did not fully capitalize the land tax. In this sense, our model provides a lower bound on the economic effects of a land tax.

TABLE D.2

LAND VALUES.

	Home value growth		Land price post minus pre period		Land price growth (Morris et al., 2021)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS (full sample, growth from 2000–2020)						
ILT	0.030	0.603**	-0.059	-0.077	-0.158	-0.070
	(0.977)	(0.018)	(0.684)	(0.612)	(0.817)	(0.923)
State Fixed Effects	Y	Y	Y	Y	Y	Y
Year-2000 controls		Y		Y		Y
N	2045	2036	1324	1314	787	787
R2	0.000	0.507	0.052	0.060	0.445	0.519
Panel B: IV estimates (precise subsample, 2010–2020)						
ILT	2.841	0.830	4.084***	4.331***	1.734	1.839
	(0.434)	(0.792)	(0.000)	(0.001)	(0.808)	(0.804)
State Fixed Effects	Y	Y	Y	Y	Y	Y
Year-2000 controls		Y		Y		Y
N	1136	1130	912	905	421	421
First-Stage F Statistic	25.245	21.209	21.268	18.375	10.206	9.553

This table presents estimates of the effect of the implicit land tax on various measures of land prices and property values. In columns 1 and 2, the dependent variable is median home value, provided by NHGIS. In columns 3 and 4, the dependent variable is the change in our marginal land value estimate (δ_1) between the Pre and Post period. In columns 5 and 6, the dependent variable is growth in the average land values between 2012 and 2019, based on the data from Davis et al. (2021). Standard errors, clustered at the state level, are reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.001 levels.

tures for land. This is the same condition that leads to the very strong growth effects that we observe empirically. Therefore, our study offers some reassurance for land-owners in locations that are considering shifting the property tax burden toward land.

TABLE D.3

DENSITY-DEPENDENT EFFECTS ON LAND PRICES AND POPULATION DENSITY GROWTH (IV ESTIMATES, NONRESTRICTIVE COUNTIES).

	Home value growth	Land price post minus pre-period	Land price growth (Morris et al., 2021)	Population density growth
	(1)	(2)	(3)	(4)
ILT (Post Period)	2.923**	0.726	18.130	3.134**
	(0.021)	(0.216)	(0.103)	(0.020)
ILT (Post) X (log) density 2000	31.394**	10.986*	146.366	37.962***
	(0.013)	(0.093)	(0.122)	(0.006)
State Fixed Effects and density controls	Y	Y	Y	Y
N	1171	961	351	1171
Kleibergen-Paap LM test	11.509	9.205	5.226	11.509

This table presents estimates of density-dependent effects of the implicit land tax. Density is population-weighted. Year-2000 density is included as a control, but its coefficient estimate is not reported. The Post-period ILT and its interaction with (log) density are instrumented with the Pre-period ILT and its interaction with (log) density. The sample excludes counties with above-median values of the Wharton Land Use Regulation Index. *, **, and *** indicate significance at the 0.1, 0.05, and 0.001 levels.

D.4. *Within-county population distribution*

Here, the model is extended to permit the population to move across separate residential locations within a county: a downtown characterized by a fixed supply of land and a suburb characterized by an elastic supply of land. As discussed in Section 5, this extension serves two purposes. First, it helps formalize our empirical evidence that land taxes induce the concentration of the population within counties. Second, it allows us to examine the effect of a land tax that is imposed on both locations, which is indicative of the effects of a national land tax. In other words, the model extension offers a guide to the sorting effects of a land tax imposed across the *country*; the downtown represents large cities with inelastic housing supply, and the suburb represents all other areas with larger housing supply elasticities. If we were to impose a tax only on the downtown location, then this model extension would be similar to the baseline single-location model above but with an explicit derivation for demand for living in downtown (rather than the reduced-form population demand equation given in equation (14)).

To accommodate this model extension, we assume that households have preferences over downtown housing H_D and suburban housing H_S. In particular, household housing consumption is

$$H = \left(H_D^{\frac{\sigma-1}{\sigma}} + H_S^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{20}$$

where H_D and H_S are comprised of land and structures as given by equation (12).[3] The household's budget constraint is now

$$I + \xi \sum_{\ell \in \{D,S\}} r_\ell \overline{L}_\ell + \kappa \overline{T} = \sum_{\ell \in \{D,S\}} r_\ell L_\ell (1 + \tau_L) + \sum_{\ell \in \{D,S\}} p_S S_\ell (t + \tau_S) + C, \tag{21}$$

where subscript ℓ indexes the location (downtown or suburb).

Finally, L_D is fixed, and, following Couture et al. (2021), we assume a reduced-form land supply in the suburbs:

$$L_S = r_S^{\varphi}. \tag{22}$$

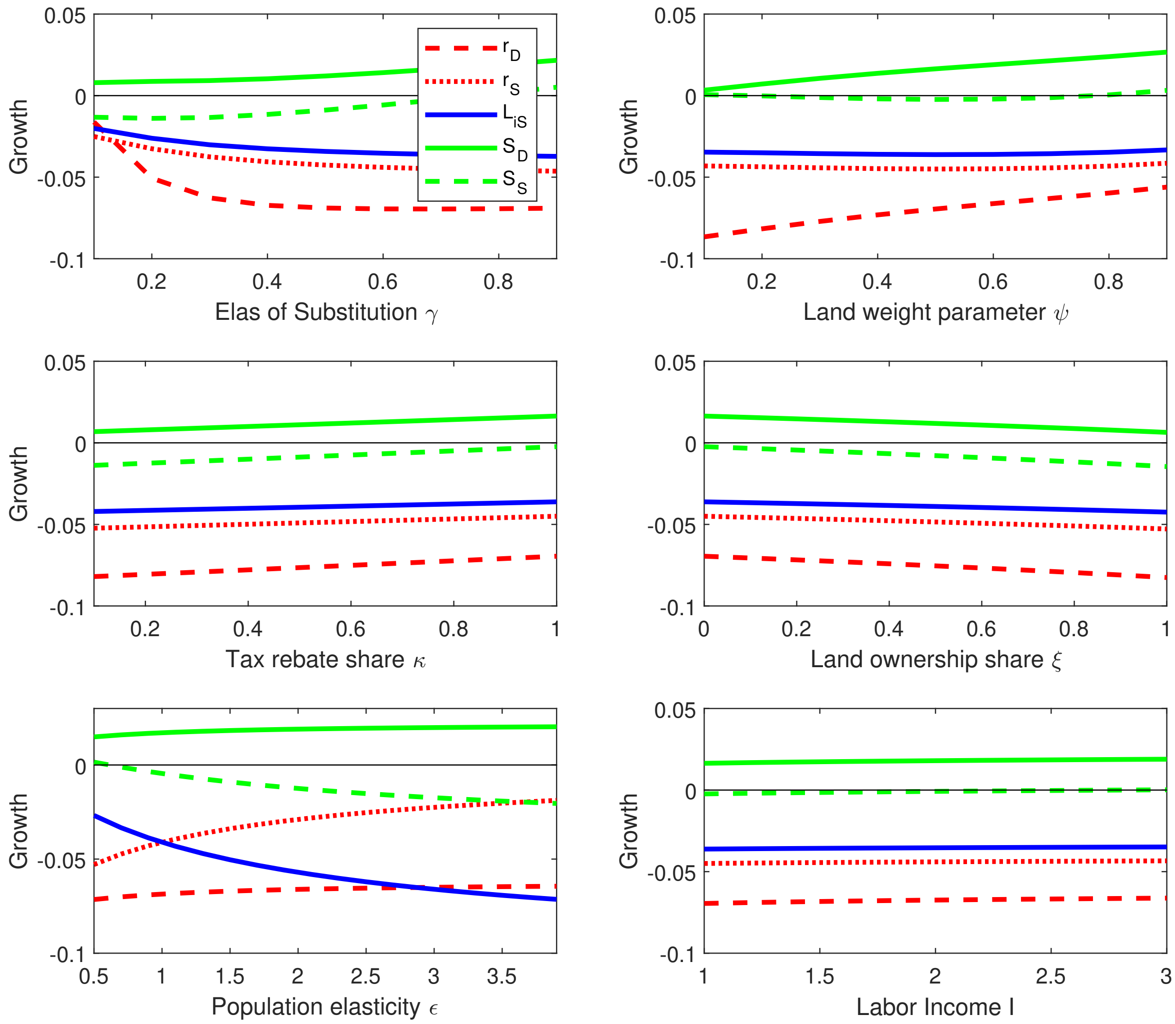
In Figure D.4, we show the effects of a ten percent land tax under the same baseline parameter values as above (along with $\varphi = 2.3$ – the median housing supply elasticity across counties). To interpret the effects, it is helpful to refer back to the effects of a land tax imposed in a single location (Figure 5). A higher land tax reduces the price of land. According to Figure D.4, the land price falls more in the downtown location, as land is inelastically supplied there and, therefore, requires a larger decline in its price to clear the land market.

Suburban land prices decline (albeit less) due to the higher land tax. The lower value of suburban land leads to less land development and, hence, a lower residential footprint of the county (country).

The lower residential footprint of the county implies a greater concentration of the population. Both downtown and the suburbs experience an increase in the ratio of structures-to-

[3] An alternative to modeling identical households with CES preferences would be to assume heterogeneous households with discrete location choices, as in Couture et al. (2021).

FIGURE D.4.—Effect of a land tax across downtown and suburban locations



land[4] indicating that both locations experience an increase in population density. It follows that population-weighted density across the county increases.

[4]In the suburbs, residential land falls by more than structures, implying an increase in structural density.

APPENDIX E: ADDITIONAL EMPIRICAL TESTS

This section presents additional tests including Appendix Tables referenced in the main text. Table E.1 demonstrates the independence of the *implicit land tax* and county characteristics, as discussed with respect to Figure 1 in Section 2. We also explore other dimensions of heterogeneity. In Appendix D.3 and Table D.1 we examined whether the effects of the *implicit land tax* are stronger in denser counties and Table E.2 considers heterogeneity with tax assessor characteristics. Table E.3 considers heterogeneity in the efficient provision of public services Finally, Table E.4 presents our baseline estimates with CBSA fixed effects rather than state fixed effects.

TABLE E.1

LAND TAXES AND CORRELATIONS 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. The land price estimate of δ_1 described in Section 2. Other variables are year-2000 log-levels.

TABLE E.2

TAX ASSESSOR CHARACTERISTICS, THE ILT, AND DENSITY GROWTH

Panel A: Assessor Characteristics and the ILT				
	Share of counties with characteristics	Dependent variable: ILT (full Sample)		
	(1)	(2)	(3)	(4)
Elected Assessor	0.47	-0.003		
		(0.002)		
Uses Algorithm	0.83		-0.004**	0.002
			(0.002)	(0.002)
State Fixed Effects				Y
N	2376	1985	2047	2047
R2		0.016	0.017	0.216

Panel B: Assessor Characteristics and the effect of the ILT on population growth				
	Dependent Variable: population growth			
ILT	1.902**	2.092***	2.612**	2.217
	(0.734)	(0.579)	(1.271)	(1.652)
ILT X Elected	-0.894	-0.262		
	(1.411)	(0.759)		
ILT X Algorithm			-1.357	-0.349
			(1.511)	(1.700)
Elected	-0.007			
	(0.030)			
Algorithm			-0.022	0.042**
			(0.022)	(0.017)
State Fixed Effects		Y		Y
N	1985	1985	2045	2045
R2	0.010	0.227	0.011	0.225

This table examines the relationship between tax assessor characteristics, the ILT, and population density growth from 2000 to 2020. The characteristics are indicators of whether the jurisdiction has an elected assessor and whether the jurisdiction assigns tax rates using an algorithm. Column 1 of Panel A reports the share of counties with positive indicators for each characteristic. Columns 2 through 4 report coefficient estimates from a regression of the ILT on the indicators. The indicator for elected assessor varies by state and is absorbed by state fixed effects. Panel B reports estimates from regressions of population density growth on the ILT and its interaction with the assessor indicators. In Panel B, columns 2 and 4 include state fixed effects. Standard errors, clustered at the state level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.2 examines relationships between the tax assessor characteristics, the ILT, and the effect of the ILT on population growth. Panel A reports the dependence of the ILT on assessor characteristics. Nearly half of jurisdictions have an elected assessor, and over 80% of assessors use an algorithm (column 1). According to column 2, there is no detectable relationship between the ILT and whether the assessor is elected. According to column 3, using an algorithm is associated with a slightly lower ILT, although this characteristic accounts for a negligible amount of the variation in the ILT (r-squared=0.017). In addition, this relationship is fully absorbed by state fixed effects (column 4).

Panel B examines whether the effect of the ILT on density growth varies with assessor characteristics. Each column presents estimates from a regression of 2000–20 density growth on the ILT, on tax assessor characteristics, and on their interaction. For each specification, the interaction term is statistically indistinguishable from zero.

Next we assess whether land taxes have stronger growth effects when revenues yield strong benefits to local residents (e.g., through efficient provision of public services). We use several proxies for the efficient provision of public services and report how the growth effect of the *implicit land tax* depends on these proxies in Appendix Table E.3. First, we use estimates from O'Loughlin and Wilson (2021) on what regions had more efficient local governments. We examine differential growth effects for the entire 2000–2020 period (Panel A) and—to limit potential reverse causality from economic growth to government efficiency—for the latter 2010–2020 period. We report in columns 1 and 2 that the land tax is more effective in these efficient regions and that the differential is statistically significant under most specifications.

Second, we use whether the county resides in a Truth-in-taxation state, which could be associated with incentives for jurisdictions to be more efficient with tax revenues. Truth-in-taxation states indeed exhibit stronger effects of the *implicit land tax*, although the differences are not statistically significant (columns 3 and 4). Finally, we create an indicator for whether U.S. News and World Report identifies the county as having effective local government based on surveys of resident perceptions.[5] Columns 5 and 6 indicate that these states tend to exhibit stronger effects of the *implicit land tax*.

[5] https://www.usnews.com/news/best-states/articles/2019-05-14/people-in-these-states-think-their-government-is-most-effective

TABLE E.3

LAND TAXES AND EFFECTIVE PUBLIC PRODUCTION

	Dependent Variable: Population Density Growth 2000–2020					
	(1)	(2)	(3)	(4)	(5)	(6)
ILT	0.898	-0.006	1.398**	1.529*	0.898	0.819***
	(0.751)	(0.385)	(0.689)	(0.761)	(0.751)	(0.294)
ILT X Effective Region	1.322	1.448**				
	(0.857)	(0.542)				
ILT X TruthInTaxation			1.015	0.390		
			(0.783)	(0.893)		
ILT X Effective State					1.543	3.058***
					(1.495)	(0.604)
Year-2000 controls		Y		Y		Y
Zip Fixed Effects		Y		Y		Y
State Fixed Effects	Y	Y	Y	Y	Y	Y
N	2045	2039	2045	2048	2045	2039
R2	0.225	0.402	0.225	0.225	0.224	0.403

This table reports coefficients from county-level regressions of growth in population density between 2000 and 2020 on the ILT (computed using the Sales-Only method). The year-2000 controls include (log of) population density, population-weighted density, labor earnings, establishments, and diversity. Standard errors, clustered at the state level, are reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.001 levels.

Finally, we provide estimates using CBSA-fixed effects instead of state-fixed effects. These estimates provide additional robustness to our estimates. Our baseline estimates suggest population density growth between 2000 and 2020 increased by 1.919% when we control for state-fixed effects (column 2 Table IV). With CBSA-fixed effects, the estimate is 1.977% (column 3 Table E.4). The similarity in the estimates in Table E.4 and Table IV limit the potential effect of unobserved factors at a finer geographic level on our estimates. The other columns of Table E.4 demonstrates similar estimates for the sales only and machine learning samples, using the *implicit land tax* measured in the pre-period and the full sample.

TABLE E.4

LAND TAXES AND POPULATION DENSITY (CBSA FIXED EFFECTS)

	Sales Only			Machine Learning		
Population Density Growth Period	2010–2020	2000–2020		2010–2020	2000–2020	
	(1)	(2)	(3)	(4)	(5)	(6)
Implicit Land Tax (Pre Period)	0.802***	1.485**		0.964***	1.377*	
	(0.269)	(0.729)		(0.344)	(0.756)	
Implicit Land Tax (Full Sample)			1.977**			1.800***
			(0.870)			(0.667)
CBSA Fixed Effects	Y	Y	Y	Y	Y	Y
N	1270	1269	1388	1334	1333	1443
R2	0.742	0.716	0.712	0.736	0.703	0.704

This table reports coefficients from county-level regressions of growth in population density on the *Implicit Land Tax*. Columns 1 through 3 are based on the sales-only method of computing the ILT, and columns 4 through 6 are based on the machine-learning method of computing the ILT. All regressions include CBSA fixed effects. Standard errors, clustered at the state level, are reported in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.001 levels.