The Welfare Effects of Local Property Taxation*

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Abstract

In the United States, local public goods are primarily financed through property taxes. Despite their ubiquity, property taxes are distortionary relative to head taxes. This paper develops a spatial equilibrium model to quantify the welfare effects of local property taxation. I estimate an elasticity of substitution for housing of 0.27, rejecting a common assumption that households have unit elastic demand for housing. Counterfactual simulations show that switching to head taxes increases housing supply by 2%, but decreases equity and increases income segregation. Under a property tax system, low-income households receive implicit transfers of approximately \$1,900, whereas high-income households pay \$5,100. Redistribution through a progressive tax system is significantly constrained by high-income household mobility.

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1 Introduction

Local governments in the United States heavily rely on property taxes to fund public services such as education and law enforcement. Property taxes constitute a cornerstone of local public finance, generating $630 billion in tax revenue for state and local governments in 2021. Property taxes are the single largest source of tax revenue for state and local governments–exceeding both sales taxes and income taxes–and represent approximately 30% of all municipal revenue (Census of Government 2021). The centrality of property taxes in funding public goods reflects America's long historical tradition of fiscal decentralization.

Despite their fiscal importance, property taxes have conventionally been viewed as second-best taxation instruments in public finance theory. Since Oates (1972) and Hamilton (1975), economists have long recognized that property taxes are distortionary relative to head taxes.[1] In particular, property taxes function as a consumption tax on housing, creating deadweight loss by reducing housing demand. However, property taxes are also implicitly redistributionary: in the same tax jurisdiction, higher-income households typically consume more housing, therefore paying more in property taxes despite receiving similar public services. The magnitude of economic inefficiency generated by property taxes as well as their equity implications remain empirically understudied.

This paper quantifies the welfare effects of local property taxation and evaluates the equity-efficiency tradeoff inherent in property tax systems. To study local property taxation, I construct a comprehensive national dataset that enables observation of housing consumption and property tax burdens across household demographic groups. Specifically, I combine historical property transaction and tax assessment records from CoreLogic with household income information from the Home Mortgage Disclosure Act database. I further use spatial maps that provide geographic boundaries for the universe of local governments in the U.S. to identify tax jurisdictions.

I begin by presenting novel, stylized facts about local property taxation, including the spatial distribution of property tax rates and measures of nominal intrajurisdictional redistribution. I highlight three facts in particular:

1. Property taxes exhibit large interstate and intrastate heterogeneity. States differ widely in their reliance on property taxes, with mean effective tax rates ranging from a minimum of 0.4% in Hawaii to a maximum of 2.8% in New York. Intrastate variation in tax rates reflect the fragmented nature of local governance in the U.S., where counties, municipalities, and special districts independently levy property taxes. Within a metropolitan area, tax rates are 15% higher in neighborhoods closer to central business districts, suggesting differentiation in public services consistent with Tiebout (1956).

[1] Head taxes are lump-sum taxes that charge a fixed amount per capita for residence in a given neighborhood. In the U.S., California is the only state that levies lump-sum taxes on property.

2. Local governments dynamically adjust tax rates to maintain stable property tax revenue over time. For example, house prices collapsed during the financial crisis of 2007-08, and gradually recovered in the subsequent years. Despite house prices experiencing a bust-boom cycle, the amount of property tax collected for a given parcel remained stable from 2007 to 2021.

3. In the same tax jurisdiction, households pay substantially different amounts of property taxes despite receiving similar public services. Households in the bottom quartile of income pay $1,000 less in property taxes than the average household in their jurisdiction. In contrast, households in the top quartile of income pay $2,075 more in property taxes than the average household in their jurisdiction. This implicit redistribution occurs through two margins: higher-income households consume both a greater quantity of housing as well as better quality housing.

Next, I develop a spatial equilibrium model to comprehensively evaluate the welfare impacts of local property taxation. The set-up adopted is a variant of the classic Rosen (1979) and Roback (1982) framework, but I extend the model to incorporate non-linear property taxes and heterogeneous preferences for housing variety. Households begin by choosing a neighborhood to reside in, with each neighborhood providing an excludable public good funded via property taxes.[2] Households have constant elasticity of substitution (CES) preferences regarding their consumption of local housing and non-housing goods. Notably, the key parameters of the model include elasticities for both the intensive margin of housing demand–i.e., the elasticity of substitution between housing and non-housing consumption—and the extensive margin of housing demand, which captures household mobility across municipalities in response to changes in house prices.

Using household revealed preferences and a novel instrumental variable strategy, I estimate that the CES elasticity of substitution between housing and non-housing consumption is 0.27 in the U.S. Therefore, I empirically reject a common assumption in the literature that households have unit elastic demand for housing (Gaubert and Robert-Nicoud 2025). Preferences for housing are non-homothetic, with higher-income households consuming less housing as a share of housing expenditure. Furthermore, I estimate that households have an outmigration elasticity of 2.7 with respect to house prices. I use a border discontinuity design that leverages variation in housing supply elasticities for identification.

Finally, I use my model to simulate household welfare under alternative tax regimes. I consider four tax regimes: (1) ad valorem property taxes; (2) head taxes; (3) universal progressive property taxes; and (4) progressive property taxes implemented by a subset of local governments.[3] Counterfactual simulations reveal important tradeoffs between equity and efficiency. Compared to head

[2] I define a neighborhood as an elementary or unified K-12 school district.

[3] Countries such as Mexico, South Korea, and Denmark have progressive property tax systems with increasing

taxes, ad valorem property taxes provide \$1,900 in implicit transfers to low-income households (i.e., households that earn less than \$25,000) while high-income households (i.e., households that earn more than \$200,000) pay \$5,100 more. Replacing ad valorem property taxes with head taxes eliminates deadweight loss and increases housing supply by 2%, but amplifies income segregation across neighborhoods. Conversely, universal progressive property taxes are more equitable than ad valorem property taxes, but at the cost of further distorting housing consumption. For instance, adopting an increasing marginal tax rate system similar to that of Denmark would increase implicit payments from high-income households by \$4,000, allowing for an additional \$500 in transfers to low-income households.[4] Income segregation is reduced across neighborhoods, but housing supply decreases by 1%. Redistribution is significantly limited by high-income household mobility unless progressive property taxes are implemented universally by local governments. When only a subset of local governments adopt progressive property taxes, high-income households vote with their feet to avoid redistribution, therefore amplifying income segregation instead.

This paper contributes to several strands of literature in public finance and urban economics. This paper most directly relates to the extensive literature on property taxes. Starting with the seminal work of Tiebout (1956), numerous papers have studied how property taxes and local public goods determine housing prices and household sorting (Oates 1969; Hamilton 1976; Brueckner 1979; Yinger 1982; Yinger et al. 1988; Fischel 2001; Lutz 2015; Koster and Pinchbeck 2022). In parallel, several papers have theoretically established that property taxes are distortionary relative to head taxes (Oates 1972; Hamilton 1975; Zodrow and Mieszkowski 1986; Ross and Yinger 1999; Calabrese, Epple, and Romano 2012; Barseghyan and Coate 2016). While the literature has established the theoretical inefficiency of local property taxation, I *empirically* quantify the magnitude of the inefficiency relative to the equity gains through redistribution.

Furthermore, existing empirical work on property taxes is often constrained to a limited sample of municipalities due to lack of centralized assessment data. A notable exception is Avenancio-León and Howard (2022), who use a national dataset to demonstrate how county assessor offices typically overvalue housing located in low-income, minority neighborhoods. I use a comprehensive national sample to provide novel, stylized facts on the spatial distribution of property taxes and their incidence by income, addressing a significant gap in our understanding of how property tax burdens vary geographically and demographically.

This paper also contributes to a substantial literature on spatial equilibrium models. Building on the foundational work of Rosen (1979) and Roback (1982), numerous papers have used spatial equilibrium models (e.g., Bayer, Ferreira, and McMillan 2007; Busso, Gregory, and Kline 2013;

marginal tax rates on property. In the U.S., the District of Columbia became the first municipality to implement increasing marginal tax rates on property in 2024.

[4] In Denmark, property is taxed at 0.51% of its value up to DKK 9,200,000 and 1.4% of the value exceeding DKK 9,200,000. That is, the marginal tax rate nearly triples when property values exceed the threshold.

Ahlfeldt et al. 2015; Diamond 2016; Suarez Serrato and Zidar 2016; Couture et al. 2021; Tsivanidis 2025) to empirically study urban policies such as place-based subsidies and transportation infrastructure investments. This paper uses a similar framework to evaluate local property taxation. However, I extend existing models by incorporating non-linear property taxes and allowing for heterogeneous preferences for housing variety.

Lastly, this paper contributes to the vast literature on consumption taxation. In particular, property taxes can be viewed as a form of consumption tax on housing. Various papers have provided a theoretical foundation for understanding when commodity taxation is optimal (Harberger 1964; Diamond 1975; Atkinson and Stiglitz 1976; Saez 2002; O'Donoghue and Rabin 2006; Chetty 2009). Others papers empirically study the economic incidence of consumption taxes on goods such as cigarettes (e.g., Adda and Cornaglia 2006), gasoline (e.g., Bento et al. 2009), and internet commerce (e.g., Einav et al. 2014).

The remainder of the paper is organized as follows. Section 2 describes the data sources used for analysis. Section 3 presents novel stylized facts about U.S. property taxation. Section 4 develops a spatial equilibrium model of housing demand and supply with property taxation. Section 5 describes the estimation strategy and presents parameter estimates. Section 6 presents counterfactual simulations comparing property taxes to alternative tax regimes. Section 7 concludes.

2 Data

I bring together data from a variety of commercial, administrative, and public sources.

2.1 CoreLogic

To study housing consumption and property taxation, I use data collected and made available by CoreLogic. In particular, I use the CoreLogic Deeds dataset and the CoreLogic Historical Property Taxation dataset. The CoreLogic Deeds dataset contains the near-universe of property transactions for all U.S. counties from 2000 to 2021, sourced from register of deeds offices. Detailed information about each transaction is collected, including: property parcel number, property address, property type, transaction closing date, transaction type, transaction price, and structural characteristics such as square footage and year built. If the transaction is associated with a mortgage, CoreLogic additionally provides detailed information about the loan, including: loan amount, loan type, and name of the lender who originated the loan. I limit my sample to transactions classified as arms-length (i.e., between unfamiliar buyers and sellers) and properties that are sold individually as opposed to a portfolio sale. Appendix Figure 1 provides a map of the counties in my sample.

The Corelogic Historical Dataset contains property tax assessments for the vast majority of U.S.

counties from 2007 to 2021, sourced from county assessor offices. Detailed information about each tax assessment is collected, including: property parcel number, property address, property type, tax year, tax jurisdiction, tax assessment value, and tax amount. Counties in my sample include 98% percent of the U.S. population, and Appendix Table 1 provides sample statistics on the counties. For my empirical analysis, I exclude counties in California; the property tax system in California is highly distorted due to Proposition 13, a California constitutional amendment that greatly limits property taxes.[5]

To geolocate each housing transaction and property tax assessment, I rely on the Nationwide Parcel Boundary map from Regrid. For each transaction and tax assessment, I match on parcel number to obtain the property's corresponding parcel boundaries. Parcel boundaries are then spatially merged with Census TIGER/Line shapefiles to observe each property's census tract, ZIP code, K-12 school district, municipality, and metropolitan area.[6]

2.2 Home Mortgage Disclosure Act (HMDA)

To observe household demographics, I merge CoreLogic data to Loan Application Register (LAR) files collected as required by the Home Mortgage Disclosure Act of 1975 (HMDA). The LAR files supply mortgage applicant data essential for monitoring potential redlining and discriminatory lending practices, including information on the race, ethnicity, gender, and household income of all applicants and co-applicants.[7] Additional housing and mortgage variables–such as transaction closing date, property census tract, loan amount, loan type, and name of the lender who originated the loan–are also reported and facilitate merging with CoreLogic data.

I follow a similar procedure in Bayer et al. (2022) to merge CoreLogic data and HMDA data. The CoreLogic and HMDA merge uses a multi-step algorithm that matches on the following key variables: transaction closing date, property census tract, loan amount, loan type, and name of the lender who originated the loan. Appendix 2 explains the algorithm in detail. As the merging procedure is fuzzy, mortgages may remain unmatched due to either having multiple matches or no matches. Overall, the performed merge is fairly successful, with approximately 57% percent of all mortgages in the CoreLogic sample uniquely matched to a corresponding mortgage application in the HMDA data. Omitting unmatched mortgages reduces my sample but does not impact my em-

[5] Proposition 13 stipulates that property assessment values can increase by no greater than 2% each year, and property taxes are limited to 1% of assessed values (plus any additional voter-approved taxes). Consequently, California is the only state in the U.S. that separately uses a lump-sum parcel tax system to raise local government revenue.

[6] In most states, K-12 school districts are unified school districts that provide both elementary and secondary education. In some states, certain areas have separate elementary and secondary school districts, each responsible for providing education to mutually exclusive grade levels. For expositional simplicity, I ignore this distinction and define a parcel's K-12 school district as its elementary or unified school district.

[7] Household income reflects pre-tax income amounts reported on mortgage applications.

pirical analysis, provided that unmatched mortgages are not systematically different from matched mortgages.

2.3 Sample representativeness

Since I only observe household income for housing transactions associated with mortgage loans, my data is limited to the income of homeowners, who typically have a higher income than renters. Figure 1 presents the distribution of household income in 2019 in the HMDA data. To benchmark the HMDA data, I compare it against two reference distributions from the 2019 American Community Survey (ACS): the national distribution of household incomes and the distribution of household incomes for homeowners who recently purchased their house with a mortgage.[8]

I find that the distribution of household income in my sample largely matches the distribution of household income for homeowners that recently purchased their house with a mortgage, suggesting that the income measures in the HMDA data are reliable.[9] In contrast, household income in my sample is significantly skewed higher-income compared to the national distribution. To account for the fact that homeowners have a higher average income than renters, I reweight my sample to match the national distribution of income in the ACS. This reweighting ensures that my empirical analysis is representative of the national population.

2.4 Supplementary data

I compile demographic and housing data at various geographical levels for all U.S. metropolitan areas. For income information, I rely on the Internal Revenue Service 2019 Individual Income Tax Statistics (IRS), which provides ZIP code-level data on income distributions and household characteristics. To assess local labor demand conditions at the census tract-level, I use place of work and journey to work tabulations from the 2000 U.S. Census of Population, which detail commuting patterns and employment locations. Additionally, I incorporate national employment trends from the Quarterly Census of Employment and Wages (QCEW), which provides employment counts by industry since 1975. To measure school district-level educational outcomes, I use datasets from the Stanford Education Data Archive (SEDA), which provides standardized test measures, and the National Center for Education Statistics (NCES), which includes detailed information on school characteristics and resources. To observe revenue and expenditure data for municipalities, I use the Census of Governments, which is an annual survey of local governments and has been conducted since 1970. For housing supply elasticities at the census tract-level, I rely on the estimates pro-

[8] I define a homeowner as having recently purchased their house if they moved into their residence within the last year.

[9] Mortgage lenders will typically verify an applicant's income by requesting paycheck stubs and tax returns.

vided in Baum-Snow and Lu (2024). For measures of total factor productivity at the commuting zone-level, I rely on estimates from Card, Rothstein, and Yi (2025). Finally, I use ZIP code-level data from Zillow Housing Data (Zillow) to observe average house prices and rents.

In addition to these datasets, I also compile information on aggregate consumption trends to understand household spending behavior. Specifically, I use the 2019 Consumer Expenditure Survey (CEX) to estimate average housing expenditure shares by income level. To account for the impact of taxation and government transfers on household budgets, I use the Supplemental Poverty Measures from the 2019 American Community Survey (ACS), which translate pre-tax income into post-transfer resources. To construct ZIP code-level price indices for non-housing goods, I use the Nielsen Homescan data, which surveys a nationally representative panel of households on their purchases of groceries and consumer packaged goods (e.g., snacks and personal care products).

Finally, I use data from Infutor to observe household migration. The Infutor database provides the entire address history for more than 300 million US residents.[10] This data was first described and made use of by Diamond, McQuade, and Qian (2019). Appendix 3 provides more detail on the supplementary datasets used.

3 U.S. property taxation

3.1 Setting

Local public goods in the U.S. are heavily funded by local property taxation. Figure 2 presents the share of local government revenue from different sources from 1970 to 2021 according to the Census of Governments. Historically, property taxes have accounted for approximately one-third of all local government revenue. The bulk of the remaining revenue has traditionally derived from state and federal intergovernmental transfers, making property taxes the single largest source of tax revenue for local governments. Approximately $630 billion of state and local property taxes were collected in 2021, establishing housing as one of the most heavily taxed goods in the U.S. Furthermore, revenue raised from property taxes is largely used to fund elementary and secondary education. According to the 2019 Census of Governments, at least 46 percent of property taxes collected by local governments were allocated to K-12 school districts.[11]

Property taxes are levied annually based on three factors: a parcel's property tax rate, property

[10] Infutor is a data aggregator of address data using many sources including phone books, magazine subscriptions, and credit header files.

[11] In 2019, 46 percent of property taxes collected by local governments were allocated to independent K-12 school districts. In many municipalities, such as New York City and Boston, school districts are not separate government entities. In such cases, I cannot observe the amount of property taxes allocated to those school districts, meaning 46 percent is an underestimate for the share of property taxes allocated to K-12 school districts.

value, and assessment ratio.[12] Local governments–which consist of counties, municipalities (e.g., cities), and special districts (e.g., school districts)–have independent authority in setting property tax rates. A parcel's property tax rate is determined by its local tax jurisdiction, which consists of the combined local government entities that oversee it. County assessor offices determine property values, collect all property taxes, and appropriately distribute tax revenue to local governments. In the majority of states, property values are legally mandated to reflect fair market value–i.e., how much the property would sell for in an open market.[13] Assessment ratios, typically established by state legislatures, are used to convert property values into assessment values.

As an example, suppose a property valued at $1 million is located in a state with an assessment ratio of 0.5 and a local tax jurisdiction with a tax rate of 1%. Every year, the property owner would be responsible for paying $5 thousand in property taxes. To calculate effective property tax rates for each parcel, I manually collect assessment ratios from state statutes. I define an effective property tax rate as the corresponding property tax rate if property values were adjusted such that each state used an assessment ratio of 1. In the example above, this would translate to an effective tax rate of 0.5%.

3.2 Stylized facts about property taxes

Property tax rates are highly heterogenous, demonstrating both significant interstate and intrastate variation. Panel A of Figure 3 presents the distribution of mean residential property tax rates aggregated at the state level. Panel B of Figure 3 depicts the distribution of residential property tax rates after residualizing by state-specific mean values, thereby isolating within-state variation. States differ widely in their reliance on property taxes, with mean effective property tax rates ranging from a minimum of 0.4% in Hawaii to a maximum of 2.8% in New York.

Substantial intrastate variation in property tax rates reflect the fact that local governments are highly fragmented in the U.S, where counties, municipalities (cities, towns, etc.), and special districts (school districts, water districts, etc.) independently levy property taxes. Boundaries for different levels of local governments are typically congruent, but exceptions exist. Figure 4 presents an example from Schönholzer (2024), where boundaries for two level of local governments, municipality and school district, are misaligned. In this example, parcels belong to one of three tax jurisdictions: (1) Santa Clara County/Cupertino City–Cupertino Union School District; (2) Santa Clara County–Saratoga City–Cupertino Union School District; and (3) Santa Clara County–Saratoga City–Saratoga Union School District.[14] In practice, K-12 school districts generally characterize

[12] A parcel is a distinct, legally defined piece of real estate.

[13] Assessor offices typically use prior sales transactions to predict the market value of all properties.

[14] I refer to the specific combination of county, municipality, and special districts that a parcel belongs to as its tax jurisdiction.

the smallest unit of local government and receive a majority of the property taxes collected in a tax jurisdiction.[15] Hence, to a first order approximation, property taxes can be characterized as an ad valorem tax with the tax rate set by school districts.

To empirically verify the above characterization, I conduct the following variance decomposition: I run separate regressions of parcel-level property tax rates on different levels of government and calculate the variance in property tax rates explained by each level. That is, I estimate the following regression equation:

$$y_i = \lambda_{g(i)} + \varepsilon_i$$

where y_i is the property tax rate for residential parcel i in 2019 and $\lambda_{g(i)}$ is a fixed effect for a given level of government (e.g., county, municipality, school district). Figure 5 presents the results of those regressions. Approximately 86% of variation in property tax rates are explained by school district fixed effects whereas 87% of variation in residential property tax rates are explained by tax jurisdiction fixed effects.[16] Consequently, I define a local goverment as a K-12 school district for simplicity when developing my spatial equilibrium model.

To examine spatial patterns within metropolitan areas, Figure 6 presents a binscatter analysis correlating property tax rates with percentile of distance from the nearest central business district.[17] Notably, the percentile of distance from the nearest central business district is calculated relative to each metropolitan area, ensuring balanced representation in metropolitan areas across percentiles. Property tax rates are higher in neighborhoods closer to central business districts, suggesting Tiebout (1956) differentiation between local governments in the public services offered. Local governments located near central business districts set property tax rates that are approximately 15% higher than average.

Local governments generally adjust property tax rates so that per parcel revenue remains stable over time. Despite house prices experiencing a bust-boom cycle, the amount of property tax collected for a given parcel kept consistent from 2007 to 2021. Figure 7 presents house price, property value, tax rate, and tax amount indices from 2007 to 2021. To construct my house price index, I follow the repeat sales methodology from Case and Shiller (1987). To construct my property value, tax rate, and tax amount indices, I used a modified version of the repeat sales methodology, where I use repeat tax assessments instead. House prices collapsed during the financial crisis of 2007-08, and gradually recovered in the subsequent years; in contrast, the amount of property tax collected

[15]Populous cities are typically served by a single K-12 school district that exclusively serves the municipality. However, as demonstrated with Figure 4, school districts may encompass multiple municipalities, and municipalities may encompass multiple school districts.

[16]Tax jurisdiction fixed effects only explain 87% of variation in property tax rates due to tax exemptions. For example, some states have a homestead exemption, where the taxable value of a given property is reduced by a lump-sum amount if the property is the primary residence of the owner.

[17]I define as a central business district the collection of census tracts categorized as business districts in the 1982 Census of Retail Trade.

for a given parcel remained stable. In practice, local governments raise property tax rates when property values decline and decrease rates when values rise.[18] Local governments typically hold legislative sessions where legislators use anticipated property values provided by county assessor's offices to determine property tax rates that meet a desired revenue level.

3.3 Nominal intrajurisdictional redistribution

Property taxes are implicitly redistributive since within a local tax jurisdiction, different households can pay different amounts of taxes despite receiving the same public services. For instance, within a K-12 school district, higher-income households typically live in more expensive housing and therefore pay more property taxes, but all households have access to the same public schools. To characterize nominal intrajurisdictional redistribution, I calculate the difference in tax amount paid by households of different income levels relative to the mean tax amount paid by households in the same school district. Specifically, for each parcel for which I observe household income, I first residualize its 2019 tax payment by the mean 2019 tax payment in its school district. I then estimate the regression equation:

$$y_i - \bar{y}_{s(i)} = \lambda_{w(i)} + \varepsilon_i \tag{1}$$

where y_i is the tax payment for parcel i in 2019, $s(i)$ is the school district that parcel i belongs to, and $\lambda_{w(i)}$ are household income percentile fixed effects.[19] Figure 8 presents the coefficients on household income percentile fixed effects from equation (1). I find that households in the bottom quartile of income pay \$1,000 less in property taxes than the average household in their school district. In contrast, households in the top quartile of income pay \$2,075 more in property taxes than the average household in their school district.

This implicit redistribution occurs through two margins: higher-income households consume both more housing as well as better quality housing. To quantify the two margins, I estimate the regression equation:

$$y_i = \gamma_{s(i)} + \lambda_{w(i)} + \varepsilon_i \tag{2}$$

where y_i is an outcome for transaction i in 2019, $\gamma_{s(i)}$ are school district fixed effects, and $\lambda_{w(i)}$ are household income group fixed effects. Figure 8 presents the coefficients on household income group fixed effects from equation (2), where y_i is log house square footage and log price per square

[18] Despite the fact that property values are supposed to reflect fair market value in the majority of states, I find that property values imperfectly co-vary with house prices. This is driven by several factors: for example, many county assessor's offices only reassess property values biannually or triannually.

[19] Household income percentiles are defined using the national distribution of household income in the 2019 American Community Survey

feet. First, higher-income households consume more housing within the same school district: households that earn more than \$200,000 purchase houses that are approximately 58% larger in square footage than households that earn less than \$25,000. Second, higher-income households consume better quality housing: households that earn more than \$200,000 purchase houses with an approximately 40% premium in price per square feet than households that earn less than \$25,000.

Of course, the nominal incidence of property taxes does not necessarily reflect the economic incidence of property taxes given that housing prices are determined in equilibrium. In order to understand the welfare effects of property taxes, I develop a structural model of housing demand and supply.

4 Model

I develop a spatial equilibrium model allowing for a welfare analysis of local property taxation. The set-up adopted is a variant of the classic Rosen (1979) and Roback (1982) framework, but I extend the model to incorporate local property taxation and heterogeneous preferences for housing variety.

4.1 Housing demand

Assume a unit measure of heterogeneous households, where household differ according to their type θ.[20] Households choose where they may live from J neighborhoods, where residence in neighborhood j requires paying a lump-sum tax of T_j. Given residence in neighborhood j, households earn wage $w_{\theta j}$, locally consume low-quality housing h_{Lj}, which has a price r_{Lj} and ad valorem tax τ_j; high-quality housing h_{Hj}, which has a price r_{Hj} and ad valorem tax τ_j; and a non-housing good c_j, which has a price p_j. Households gain utility from a neighborhood-specific bundle of amenities A_j, as well as an idiosyncratic preference shock ε_{ij} with scale parameter σ. Households have a nested constant elasticity of substitution (CES) preference over housing and non-housing consumption:

$$u_{ij} = \frac{\eta}{\eta-1}\log\left(\alpha_\theta\alpha_j\left(h_{Lj}^{\delta_{\theta j}}h_{Hj}^{1-\delta_{\theta j}}\right)^{\frac{\eta-1}{\eta}} + c_j^{\frac{\eta-1}{\eta}}\right) + \beta_\theta A_j + \sigma\varepsilon_{ij}$$

subject to budget constraint:

$$w_\theta - T_j = r_{Hj}\left(1+\tau_j\right)h_{Hj} + r_{Lj}\left(1+\tau_j\right)h_{Lj} + p_j c_j$$

[20]For empirical implementation, household types are defined by household income. Descriptive evidence suggests that household income is a sufficient statistic for housing demand. Appendix 3 provides more detail.

Notably, households have heterogeneous preferences for housing variety. The parameter $\delta_{\theta j}$ governs neighborhood-specific *tastes* by type θ households for low-quality versus high-quality housing consumption. The parameters $\alpha_\theta \alpha_j$ govern the neighborhood-specific *appeal* of housing relative to non-housing consumption for type θ households.[21] Therefore, households implictly have non-homothetic preferences for housing consumption.

Each household's optimized utility function can be expressed as an indirect utility function v_{ij} for living in neighborhood j: given residence in neighborhood j, household i derives utility:

$$v_{ij} = \frac{1}{\eta - 1} \log \left(\left(w_\theta - T_j \right) \left(\alpha_\theta^\eta \alpha_j^\eta \tilde{r}_{\theta j}^{1-\eta} \left(1 + \tau_j \right)^{1-\eta} + p_j^{1-\eta} \right) \right) + \beta_\theta A_j + \sigma^{-1} \varepsilon_{ij}$$

where:

$$\tilde{r}_{\theta j}^{1-\eta} = \left(\frac{r_{Hj}}{1 - \delta_{\theta j}} \right)^{1-\delta_{\theta j}} \left(\frac{r_{Lj}}{\delta_{\theta j}} \right)^{\delta_{\theta j}}$$

is a household type-specific price index for housing. Households choose to live in the neighborhood that maximizes their indirect utility function.

4.2 Housing supply

Assume that each neighborhood j has a representative landowner. The landowner can produce low-quality housing and high-quality housing with marginal costs

$$c_{Hj}(x) = {H_{Hj}^0}^{-\frac{1}{\gamma_{Hj}}} x^{\frac{1}{\gamma_{Hj}}}$$
$$c_{Lj}(x) = {H_{Lj}^0}^{-\frac{1}{\gamma_{Lj}}} x^{\frac{1}{\gamma_{Lj}}}$$

Assume landowners are price-takers. Then, total supply for high-quality housing H_{Hj} and low-quality housing H_{Lj} is characterized by

$$\log\left(H_{Hj}\right) = \log\left(H_{Hj}^0\right) + \gamma_{Hj} \log\left(r_{Hj}\right)$$
$$\log\left(H_{Lj}\right) = \log\left(H_{Lj}^0\right) + \gamma_{Lj} \log\left(r_{Lj}\right)$$

The parameters γ_{Hj} and γ_{Lj} can be interpreted as the supply elasticities for high-quality housing and low quality housing, respectively.

[21] We assume log-additive separability by type in the neighborhood-specific appeal of housing (i.e., $\log\left(\alpha_{\theta j}\right) = \log\left(\alpha_\theta\right) + \log\left(\alpha_j\right)$), an assumption that I directly test in the data.

4.3 Labor

Households can provide labor in the neighborhood they live in, where the amount of labor provide is dependent on their type:

$$\ell_{ij} = \theta$$

Firms in neighborhood j produce a tradable intermediate good with a constant returns to scale production function $F\left(K_j, B_jL_j\right) = B_jL_jf\left(\frac{K_j}{B_jL_j}\right)$, where K_j and L_j refer to total (non-land) capital and labor, respectively and B_j is the local productivity level. Cost of capital is fixed at ρ and output is sold on a national market for a price of one. Firms equates their marginal product of capital to the cost of capital, meaning:

$$\frac{K_j}{B_jL_j} = f'^{-1}(\rho)$$

The marginal product of labor is then:

$$F_L = B_j\left[f\left(f'^{-1}(\rho)\right) - f'^{-1}(\rho)\,\rho\right] = B_jR(p)$$

I assume free entry, meaning wages equal the marginal product of labor:

$$w_{\theta j} = B_jR(\rho)\,\theta$$

4.4 Equilibrium

Each city j has a local government. To produce the vector of amenities A_j, the local government has a constant marginal cost of MC_j per household. To fund the production of amenities, the local government can charge a per-household head tax T_j as well as an ad valorem tax on housing consumption. Notably, we make two assumptions: first, the fiscal cost of an additional household is homogenous by household type.[22] Second, the fiscal cost of an additional household is constant. Existing literature is ambiguous on whether we would expect there to be increasing or decreasing returns to scale.

Local prices $\left(r_{jL}, r_{jH}\right)$ and taxes $\left(T_j, \tau_j\right)$ are set in equilibrium. Denote $h^*_{\theta Lj}$ and $h^*_{\theta Hj}$ as the demand functions for low-quality and high-quality housing for a household of type θ in neighborhood j. Denote $N_{\theta j}$ as the number of households of type θ that choose to live in neighborhood j. An equilibrium is defined by (1) market-clearing in the housing market:

[22]Among households where the head is a working-age adult, number of children attending public school is relatively constant with household income. Appendix 4 explores an extension of the model where the marginal cost of providing amentities to household is heterogeneous by household type.

$$H_{Hj} = \sum_{\theta} N_{\theta j} h^*_{\theta Hj}$$
$$H_{Lj} = \sum_{\theta} N_{\theta j} h^*_{\theta Lj}$$

and (2) a balanced budget constraint for local governments:

$$T_j + \sum_{\theta} \frac{N_{\theta j}}{\sum_{\theta} N_{\theta j}} \left(h_{\theta Lj} r_{Lj} \tau_{Lj} + h_{\theta Hj} r_{Hj} \tau_{Hj} \right) = MC_j$$

That is, equilibrium requires that supply equals demand, and the average tax raised per household equate the cost of amenity production.

5 Estimation

The key parameters of my model can be grouped into: (1) parameters that determine how much housing households consume (i.e., the intensive margin of housing demand) and (2) parameters that determine which neighborhoods households choose to reside in (i.e., the extensive margin of housing demand).

5.1 Intensive margin of housing demand

I begin by estimating parameters that govern the intensive margin of housing demand. Because I use housing transaction data to observe housing consumption, I observe house prices instead of rent prices. Following a common practice in the literature, I impute owners' equivalent rent from house prices. I assume houses are priced via discounted cash flow:

$$P = \frac{1}{\rho} (r - Pt)$$

where P is house price, r is rent price, t is the property tax rate, and ρ is the discount rate. Therefore, rents are implicitly taxed at rate:

$$\tau = \frac{P}{r} t$$

I calculate metropolitan area-level price-to-rent ratios using Zillow data on median prices and rents for single-family homes. For each metropolitan area, I divide median prices for single-family homes by median rents for single-family homes to get a price-to-rent ratio.[23] I use my imputed

[23]The Zillow data implies a national price-to-rent ratio of 12.6, consistent with price-to-rent ratios estimated in

owners' equivalent rent from house prices to estimate housing expenditure shares by income group. As a validation exercise, I benchmark my housing expenditure shares to the 2019 Consumer Expenditure Survey and find relatively similar shares by income (Figure 10).

Next, I calculate income-specific rent indices $\tilde{r}_{\theta j}$ for housing. In my model in Section 4, households choose between low- versus high-quality housing, where quality is specific to the neighborhood, and the parameter $\delta_{\theta j}$ governs neighborhood-specific taste for quality. Since I assume households have Cobb-Douglas preferences over low- versus high-quality housing, $\delta_{\theta j}$ is identified by a household's respective consumption of each housing. In particular, I compare the average price per square feet of housing consumed by type θ households relative to the price per square feet of low- and high-quality housing. With only two levels of quality, the average price of housing consumed by a household uniquely determines how much low- versus high-quality housing the household consumes. As a concrete example, suppose in neighborhood j, low-quality housing is priced at \$5 per square feet and high-quality housing is priced at \$10 per square feet. Then, if households of type θ were to consume housing at priced at \$6 per square feet, they must be consuming 80% low-quality and 20% high-quality housing. I would therefore estimate a Cobb-Douglas parameter of $\delta_{\theta j} = 0.2$ for households of type θ in neighborhood j.

Notably, I cannot identify $\delta_{\theta j}$ without ex-ante defining low- versus high-quality housing. However, the choice of definition for low- versus high-quality housing is a form a normalization due to the linear properties of the problem. I define low- and high-quality housing in a neighborhood as the average price per square feet in the bottom and top tercile of housing, respectively. Figure 11 presents the distribution of $\delta_{\theta j}$ by neighborhood that I estimate for each income group, where neighborhood is defined as a ZIP code. I find that higher income groups are monotonically more likely to consume high-quality housing.

I use my estimates of $\delta_{\theta j}$ to construct income-specific ZIP code-level rent indices $\tilde{r}_{\theta j}$ for housing using Zillow data, which provides ZIP code-level price indices for the bottom tercile (i.e., r_{Lj}) and top tercile (i.e., r_{Hj}) of housing:

$$\tilde{r}_{\theta j} = \left(\frac{r_{Lj}}{\delta_{\theta j}}\right)^{\delta_{\theta j}} \left(\frac{r_{Hj}}{1-\delta_{\theta j}}\right)^{1-\delta_{\theta j}} \tag{3}$$

I then estimate η, which determines the elasticity of subsitution between housing and non-housing consumption. This is the crucial parameter governing the intensive margin of housing demand, as it determines how households change housing consumption in response to prices. Suppose that we observe housing expenditure shares $S_{\theta j}$ for income group θ in neighborhood j in two periods t and $t+1$. Through the lens of my model, the change in housing expenditure share from

Diamond and Diamond (2024).

period t to $t+1$ is given by:

$$\Delta\log\left(\frac{S_{\theta j}}{1-S_{\theta j}}\right)=(1-\eta)\Delta\log\left(\tilde{r}_{\theta j}\right)+(1-\eta)\Delta\log\left(1+\tau_j\right)-\\(1-\eta)\Delta\log\left(p_j\right)+\eta\Delta\log\left(\alpha_\theta\right)+\eta\Delta\log\left(\alpha_j\right) \tag{4}$$

where $S_{\theta j}$ is the housing expenditure share, $\tilde{r}_{\theta j}$ is the rent index for housing, τ_j is the rental tax rate, p_j is the price of non-housing consumption, α_θ is income-specific taste for housing, and α_j is neighborhood-specific taste in housing.

I take the reduced-form equation (4) to the data, where I define θ as deciles of household income, j as a ZIP code, and Δ as the change from 2010 to 2019. Note that I directly observe housing expenditure shares $S_{\theta j}$ and rental tax rates τ_j in the CoreLogic–HMDA data, and I use my prior constructed rent indices $\tilde{r}_{\theta j}$ following equation (3). To measure changes in the price of non-housing consumption p_j, I construct price indices using the Nielsen Homescan data.[24] I additionally control for changes in the price of non-housing consumption with county fixed effects, and I control for changes in the income-specific taste for housing with income decile fixed effects.[25]

I therefore estimate η using a combination of cross-sectional and longitudinal variation in expenditure shares. A naive OLS regression of equation 4 produces a biased estimate of η, due to the standard price endogeneity concern that prices may be correlated with unobserved quality (i.e., $\tilde{r}_{\theta j}$ is correlated with α_j). For example, neighborhoods with higher housing prices may also have more modern, and thus more desirable, houses. To address price endogeneity, I instrument for changes in rent prices with ZIP-code level Bartik labor demand shocks $Bartik_j$.[26] I make the identification assumption that local labor demand shocks are uncorrelated with neighborhood-specific taste in housing $\Delta\log\left(\alpha_j\right)$. That is, I use extensive margin housing demand shocks as an instrument to estimate demand on the intensive margin for housing. Intuitively, local labor demand shocks make certain neighborhoods more desirable to live in, therefore increasing the price of housing in those neighborhoods. However, given that a household has chosen to live in such a neighborhood, I assume that local labor demand shocks do not make housing more desirable relative to non-housing consumption.

The fact that local labor demand shocks may increase income is not an exogeneity violation

[24] Appendix 5 explains how I construct changes in the price of non-housing consumption using the Nielsen Homescan data. While the Nielsen Homescan data only includes prices for groceries and consumer packaged goods, food is the third largest category of household expenditure after housing and transportation.

[25] Controlling for changes in the price of non-housing consumption with county fixed effects assume that prices of the non-housing consumption are constant within county. That is, housing prices have much more spatial variation than non-housing prices. This is a reasonable assumption given the large body of research showing uniform pricing for tradable goods–see DellaVigna and Gentzkow (2019) for a review.

[26] I construct the Bartik labor demand shocks in a similar fashion as Baum-Snow and Lu (2024). In particular, I interact ZIP code level industry shares in 2019 with national changes in employment from 2010 to 2019.

since I directly observe income and can control for non-homothetic preferences for housing with income decile fixed effects. A violation of my identification assumption would instead be, for instance, the COVID-19 pandemic. During the COVID-19 pandemic, neighborhoods with a large tech industry saw an increase in house prices as stay-at-home policies led to an e-commerce boom. However, as the tech industry was a prominent adopter of work-at-home policies, housing became more desirable relative to non-housing in neighborhoods with a large tech industry.[27]

Therefore, my estimating equation is:

$$\begin{aligned} \Delta\log\left(\frac{S_{\theta j}}{1-S_{\theta j}}\right) &= (1-\eta)\widehat{\Delta\log\left(\tilde{r}_{\theta j}\right)} + (1-\eta)\Delta\log\left(1+\tau_j\right) + \\ &\quad (1-\eta)\Delta\log\left(p_j\right) + \gamma_{c(j)} + \lambda_\theta + \varepsilon_{\theta j} \\ \widehat{\Delta\log\left(\tilde{r}_{\theta j}\right)} &= Bartik_j + (1-\eta)\Delta\log\left(1+\tau_j\right) + \\ &\quad (1-\eta)\Delta\log\left(p_j\right) + \gamma_{c(j)} + \lambda_\theta + \varepsilon'_{\theta j} \end{aligned} \tag{5}$$

where $\gamma_{c(j)}$ are county fixed effects and λ_θ are income decile fixed effects. I weight ZIP codes by their population in the 2010 Decennial Census. Table 1 presents the results of regressions corresponding to equation (5). My preferred specification (Column 4) produces an estimate of $\eta = 0.27$, which implies an elasticity of housing expenditure share with respect to price of 0.51. I therefore empirically reject a common assumption in the literature that households have unit elastic demand for housing.[28] Notably, my elasticity estimates are similar in magnitude to previous estimates in the literature.[29] Preferences for housing are non-homothetic, with higher-income households consuming less housing as a share of housing expenditure but sorting to neighborhoods with more expensive housing.

Finally, I estimate the parameters α_θ and α_j, which govern the neighborhood-specific *appeal* of housing relative to non-housing consumption for type θ households. Given an estimate of η, α_θ and α_j can be directly inverted from the data. Figure 12 presents a cross-sectional binscatter of log housing prices and log housing expenditure share by income group. Intuitively, the difference in intercept by income group identifies α_θ, whereas deviations from a slope of η identify α_j.

[27] One concern is that local labor demand shocks improve the quality of housing relative to non-housing through new construction and renovations. Appendix 6 tests this concern in detail.

[28] Notable exceptions of literature that do not assume unit elastic demand for housing are reviewed in Gaubert and Robert-Nicoud 2025.

[29] To my best knowledge, Albouy, Ehrlich, and Liu (2016), with an estimate of $\frac{\partial \log(s)}{\partial \log(p)} \approx 0.6$, is the only prior work to estimate the elasticity of subsitution for housing in the U.S. context. Albouy et al. (2016) estimates the elasticity using cross-sectional differences in housing expenditure shares without instrumenting for housing prices.

5.2 Extensive margin of housing demand

The key parameter governing the extensive margin of housing demand in my model is σ^{-1}, which characterizes the dispersion of household idiosyncratic preferences for neighborhoods. Intuitively, σ^{-1} can be interpreted as a measure of household mobility, or the outmigration elasticity of households. To estimate the extensive margin elasticity of housing demand. I use geographic variation in housing supply elasticity as a source of identification. Economic theory suggests that the extent to which housing demand shocks increase rents is dependent on housing supply elasticity. In the extreme, when housing supply is perfectly elastic, housing demand shocks have no effect on price. Therefore, comparing price changes given identical demand shocks but different supply curves allows me to trace out the demand curve, thus identifying the extensive margin elasticity of housing demand.

Formally, through the lens of my model in Section 4, housing price capitalization of local public goods is characterized by:

$$\frac{\partial \log\left(r_j\right)}{\partial A_j} \approx \frac{\sigma^{-1}}{\gamma_j + \eta + \left(1 - \eta + \sigma^{-1}\right) S} \beta \tag{6}$$

where γ is housing supply elasticity, η is the parameter governing the intensive margin elasticty of housing demand, σ^{-1} is the parameter governing the extensive margin elasticity of housing demand, S is the average housing expenditure share, and β is the average preference for local public goods. Consistent with intuition, housing demand shocks have no effect on price when housing supply is perfectly elastic

$$\gamma \to \infty \implies \frac{\partial \log(r)}{\partial A} \to 0$$

Variation in housing supply elasticity and exogenous changes in local public goods allow me to identify the outmigration elasticity σ^{-1}.

To observe exogenous changes in local public goods, I follow the empirical design in Black (1999) and exploit variation in educational quality across K-12 school district boundaries. In the U.S., K-12 schools are an *excludable* local public good, as the vast majority of property taxes go towards K-12 education, and households may only attend a school in a district if they live within the geographical boundary of the district. Therefore, discrete jumps in house prices at school district boundaries measure the price capitalization of differences in school district quality.

I quantify differences in school district quality using standardized test score data from the Stanford Education Data Archive.[30] That is, I use differences in standardized test scores as a

[30] I use the average school grade and cohort-adjusted standardized test score pooled across all subjects for a given school district.

proxy measure for exogenous housing demand shocks. I then compare houses across school district borders, controlling for tax rates and housing characteristics.[31] Crucially, I only use school district borders within the same municipality, ensuring similarity in non-education local public goods. I implement this using a regression discontinuity design that compares house prices across school district boundaries within municipalities, interacting test score differences with local housing supply elasticities.[32] The key identification assumption I make is that discrete changes in unobserved quality at school district borders within the same municipality are uncorrelated with discrete changes in housing supply elasticity–notably, zoning.

In particular, I estimate the regression equation:

$$\begin{aligned}\log(p_{it}) = {} & \beta^{-1.0} \cdot \mathbb{I}(-1km \leq Dist_{it} < -0.9km) \cdot \Delta Test_{b(i)} \times Supply_{m(i)} + \ \dots + \\ & \beta^{1.0} \cdot \mathbb{I}(1km \leq Dist_{it} < 1.1km) \cdot \Delta Test_{b(i)} \times Supply_{m(i)} + \\ & \delta X_{it} + \lambda_{b(i)t} + \varepsilon_{it}\end{aligned} \tag{7}$$

where p_{it} is the sale price per square feet for house i in year t, $Dist_{it}$ is the distance of house i to the school district border, $\Delta Test_{b(i)}$ is the change in test scores across the school district border, $Supply_{m(i)}$ is an indicator whether the municipality has above median housing supply elasticity, δX_{it} are covariates (e.g., house age, lot size, property tax rate), and $\lambda_{b(i)t}$ are border year fixed effects.

Figure 13 presents the regression coefficients for β when estimating equation (7). Figure 14 presents the regression coefficients for β when estimating equation (7) without including interaction terms for housing supply elasticity. I find that a standard deviation increase in average school district test scores increases house prices by 10% in supply inelastic municipalities. Consistent with economic theory, the price effect is reduced when housing supply is elastic: a standard deviation increase in average school district test scores increases house prices by 6% in supply elastic municipalities.

I then estimate a non-linear least square regression to identify σ^{-1}, my parameter of interest. Motivated by equation (6), I estimate the following regression equation using housing transactions

[31] I control for house age, house square footage, lot size, number of bathrooms, and number of bedrooms, and property tax rate.

[32] I use housing supply elasticities from Baum-Snow and Lu (2024).

within 0.5 kilometers of a school district border:

$$\begin{aligned}\log(p_{it}) = {} & Dist_{it} \times \mathbb{I}(Dist_{it} \geq 0km) + Dist_{it} \cdot \Delta Test_{b(i)} \times \mathbb{I}(Dist_{it} \geq 0km) + \\ & \frac{\sigma^{-1}}{\gamma_j + \eta + (1-\eta+\sigma^{-1})S}\beta \cdot \Delta Test_{b(i)} \cdot \mathbb{I}(Dist_{it} \geq 0km) + \\ & \delta X_{it} + \lambda_{b(i)t} + \varepsilon_{it}\end{aligned} \tag{8}$$

where p_{it} is the sale price per square feet for house i in year t, $Dist_{it}$ is the distance of house i to the school district border, $\Delta Test_{b(i)}$ is the change in test scores across the school district border, δX_{it} are covariates (e.g., house age, lot size, property tax rate), and $\lambda_{b(i)t}$ are border year fixed effects. I estimate equation (8) using my prior estimate of $\eta = 0.73$, and I calibrate $S = 0.3$ to match the average housing expenditure shares in my data. Table 2 presents the results: I find that $\sigma^{-1} = 9.2$, which can be approximately translated to households having a share outmigration elasticity of 2.7 with respect to house prices.[33]

Finally, I assume the distribution of household idiosyncratic preferences for neighborhoods ε_{ij} is distributed generalized extreme value, consistent with a nested logit model where school districts are nested within commuting zones. I then use household migration data from Infutor to estimate the parameters of the generalized extreme value distribution. In particular, suppose household i has the following idiosyncratic preferences for school district j in commuting zone $j \in C$ in year t:

$$\underbrace{\varepsilon_{ijt}}_{\text{EV type I}} = \xi_{iC} + \lambda_2 \underbrace{\left(\xi_{ij} + \lambda_1 \underbrace{\varepsilon_{ijt}}_{\text{EV type I}}\right)}_{\text{EV type I}}$$

Figure 15 graphically presents the nesting structure for idiosyncratic preferences. The parameter λ_1 governs the likelihood that a household chooses to move, whereas the parameter λ_2 governs where households choose to move. Notably, the marginal distribution of idiosyncratic preferences in any given year is nested logit with parameter λ_2, where school districts are nested within commuting zones. That is, the population share for school district j in commuting zone $j \in C$ in year t is given by:

[33] Diamond (2016) estimates σ^{-1} ranging from 2.1 to 4.9, though with a different model specification. A direct comparison to Diamond (2016) is difficult given that I specify a CES utility function instead of a Cobb-Douglas utility function, and household choose school districts instead of metropolitan areas. Therefore, I find that household preferences for school districts is more idiosyncratic than preferences metropolitan areas.

$$S_{jt} = \frac{\exp\left(\frac{v_{jt}}{\lambda_2}\right)\left(\sum_{k\in C}\exp\left(\frac{v_{kt}}{\lambda_2}\right)\right)^{\lambda_2-1}}{\sum_{C'}\left(\sum_{k\in C'}\exp\left(\frac{v_{kt}}{\lambda_2}\right)\right)^{\lambda_2}}$$

where v_{jt} is the *non-idiosyncratic* indirect utility for household i to live in school district j in year t. Therefore, $\lambda_2 < 1$ suggests that households are more likely to move within commuting zones than across commuting zones.

I use school district-level gross migrations flows from 2010 to 2019 to estimate the parameters λ_1 and λ_2. Intuitively, net migration identifies changes in indirect utility v_{jt} for a given school district: school districts that become more desirable over time must also experience population growth.[34] Accounting for changes in indirect utility via net migration, gross migration then identifies λ_1 and λ_2. If households typically do not move away from their original school district, this suggests λ_1 is close to zero. Conditional on moving, if households only move to new school districts in the same commuting zone, this suggests λ_2 is close to zero. I estimate $\lambda_1 = 0.158$ and $\lambda_2 = 0.389$ via method of simulated moments.[35] In particular, I use the share of households that stay in their original school districts as a moment to identify λ_1. I use the share of households that move school districts but stay in their original commuting zone as a moment to identify λ_2. Figure 16 graphically presents the moment equations I use to identify the parameters of the generalized extreme value distribution.

6 Counterfactuals

I use the structural model detailed in Section 4 to simulate household welfare under alternative tax regimes. I consider four tax regimes: (1) ad valorem property taxes; (2) head taxes; (3) universal progressive property taxes; and (4) progressive property taxes implemented by a subset of local governments.

To simulate household welfare, I use the housing demand parameters that I causally estimate in Section 5.1 (i.e., δ, η, and α) and Section 5.2 (i.e., σ and λ). I calibrate housing supply elasticities (i.e., γ) using causal estimates from Baum-Snow and Lu (2024). Additionally, I allow neighborhood-specific productivity to differ by commuting zones, where I calibrate productivity differences (i.e., β) using causal estimates from Card, Rothstein, and Yi (2025). The only remaining parameters I do not observe are neighborhood-specific amenities $\beta_\theta A_j$, which I identify by inverting income-specific population shares $S_{\theta j}$. To ensure that my household income distributions are representative of the national distribution, I use income-specific household population

[34] A Berry (1994) inversion of changes in population shares identifies changes in v_{jt}.

[35] I approximate the CDF of a three-level nested logit via Fourier inversion on the characteristic function.

shares in 2019 from the Internal Revenue Service Individual Income Tax Statistics (IRS). I convert the pre-tax incomes in the IRS data to post-tax consumption budgets using the 2019 Supplementary Poverty Measure from the American Community Survey (ACS).[36] Since my housing demand parameters are estimated from a sample of households, the observed rents and tax rates in my data may not characterize an equilibrium. Therefore, I first solve for equilibrium rents and tax rates given my estimated parameters, and then validate the model by comparing untargeted moments with empirical data. Figure 17 presents the model-implied nominal intrajurisdictional redistribution in 2019, benchmarked to observed nominal intrajurisdictional redistribution that occurred in 2019.

Next, I solve for counterfactual rents and tax rates when switching from an ad valorem property tax. Counterfactual simulations reveal several key findings. First, replacing ad valorem property taxes with head taxes eliminates deadweight loss, therefore increasing aggregate housing consumption by removing price distortions. Housing prices would increase by an average of 5% across neighborhoods (Figure 18), leading to a 2% increase in housing supply (Figure 19). However, these aggregate gains mask substantial heterogeneity–price increases would be largest in areas with inelastic housing supply and high-income residents. Second, head taxes would increase residential segregation by income (Figure 20). Segregation between high and low-income households would increase by an average of 0.1 standard deviations as measured with a dissimilarity index, primarily because the elimination of property taxes would decrease the affordability of high-income neighborhoods for low-income households. Third, the efficiency gains of implementing a head tax would come at the cost of reducing equity. Relative to head taxes, the average household in the bottom income quartile experiences a utility gain equivalent to $1,900 in annual income under ad valorem property taxes, while households in the top quartile experience a utility loss equivalent to $5,100 (Figure 21).

I then simulate counterfactual rents and tax rate for a universal progressive property tax system with increasing marginal tax rates. To implement this, I set the threshold for the increase in marginal tax rate for each school district at the status quo 75th percentile housing value for the county of the school district. I then simulate more and more progressive property tax systems. Switching from ad valorem taxes to universal progressive taxes would decrease aggregate housing consumption by increasing price distortions. For example, in the case where the marginal tax rate triples at the threshold, housing prices would decrease by an average of 2% across neighborhoods (Figure 18), leading to a 1% decrease in housing supply (Figure 19). The efficiency losses of implementing a universal progressive tax would come at the benefit of promoting equity. Relative to head taxes, the average household in the bottom income quartile experiences a utility gain equiv-

[36]The Supplementary Povery Measure uses the National Bureau of Economic Research TAXSIM to calculate net-of-tax household resources.

alent to $2,400 in annual income under universal progressive property taxes, while households in the top quartile experience a utility loss equivalent to $12,000 (Figure 22). Additionally, universal progressive taxes reduce income segregation.

Redistribution is significantly limited by high-income household mobility unless progressive property taxes are implemented universally by local governments. When only a subset of local governments adopt progressive property taxes, high-income households vote with their feet to avoid redistribution, therefore amplifying income segregation instead. I simulate counterfactual rents and tax rates for a tax regime where poor school districts adopt a progressive property tax system with increasing marginal tax rates, but rich school district adopt an ad valorem property tax. In the case where the marginal tax rate triples at the threshold, lower-income households experience almost no additional redistribution (Figure 22). Relative to head taxes, the average household in the bottom income quartile experiences a utility gain equivalent to $2,050 in annual income under partial progressive property taxes, while households in the top quartile experience a utility loss equivalent to $5,550 (Figure 22).

7 Conclusion

Local governments in the U.S. heavily rely on property taxes to fund essential public services, particularly K-12 education. Property taxes constitute a cornerstone of local public finance in the United States, generating approximately $630 billion in revenue for state and local governments in 2021. Despite their fiscal importance, property taxes introduce distortions into housing markets. Since Oates (1972) and Hamilton (1975), economists have long recognized that property taxes are inefficient relative to head taxes.

This paper quantifies the welfare effects of local property taxation and evaluates the equity-efficiency tradeoffs implicit under a property tax system. I begin by presenting novel stylized facts about property taxation, including the distribution of property tax rates across jurisdiction as well as measures of nominal intrajursdictional redistribution. First, property taxes exhibit large interstate and intrastate variation. States differ widely in their reliance on property taxes, with effective property tax rates ranging from a minimum of 0.4% in Hawaii to a maximum of 2.8% in New York. Within the same metropolitan area, property tax rates are 15% higher in local governments closer to central business districts, suggesting differentiation in the local public goods offered. Second, local governments dynamically adjust property tax rates to maintain stabilize property tax revenue over time. When property values decline or rise with house prices, local governments increase and decrease property tax rates accordingly. Third, I find that households in the bottom quartile of income pay $1,000 less in property taxes than the average household in their school district. In contrast, households in the top quartile of income pay $2,075 more in property taxes than the average household in their school district.

Next, I develop a spatial equilibrium model to quantify the welfare effects of property taxes. Crucially, I estimate a CES elasticity of substitution for housing of 0.27, rejecting the common assumption that households have unit elastic demand for housing. I then use my model to simulate household welfare under different tax regimes. I find that under the current property tax system, low-income households receive implicit transfers averaging approximately \$1,900 annually, while high-income households effectively pay premiums of approximately \$5,100. Replacing property taxes with head taxes would increase housing supply by 2% through eliminating price distortions, but would significantly reduce equity and amplify income segregation. Conversely, a more progressive property tax system would enhance equity at the cost of further distorting housing consumption. These findings suggest that the efficiency costs of local property taxation must be weighed against their redistributive benefits, explaining why property taxes are ubiquitous. Finally, redistribution via a progressive tax system is significantly constrained by high-income household mobility. Unless all local governments implement a progressive property tax, high-income households can avoid redistribution by voting with their feet.

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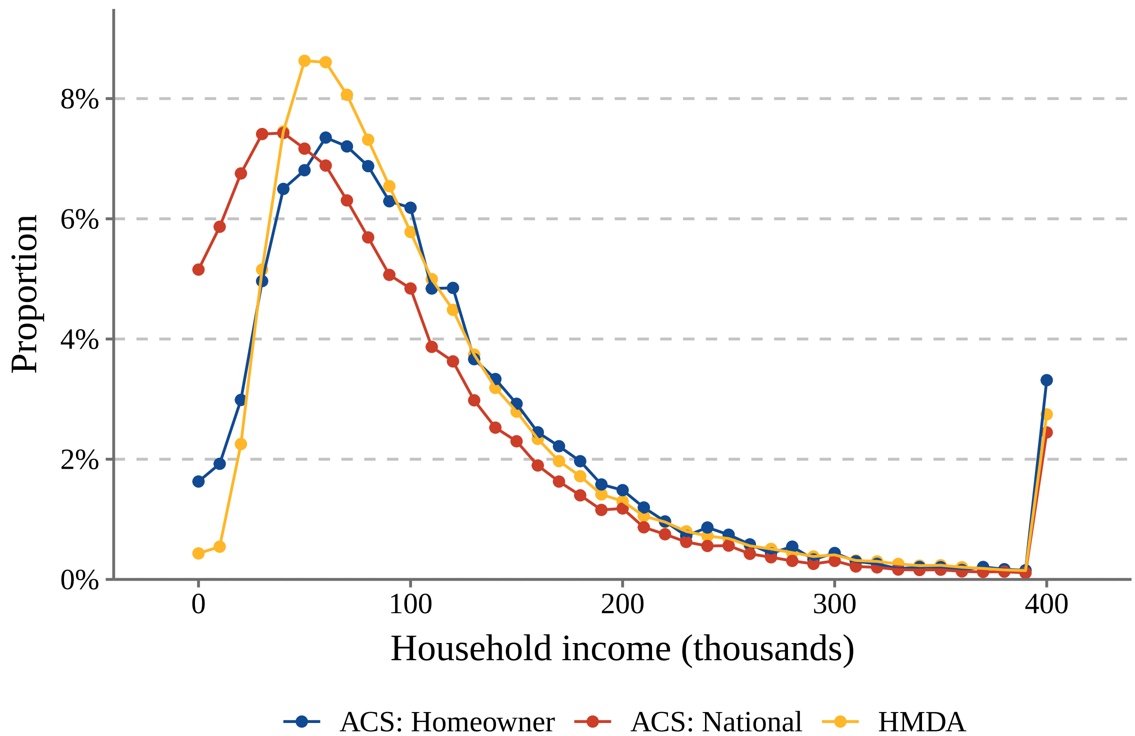
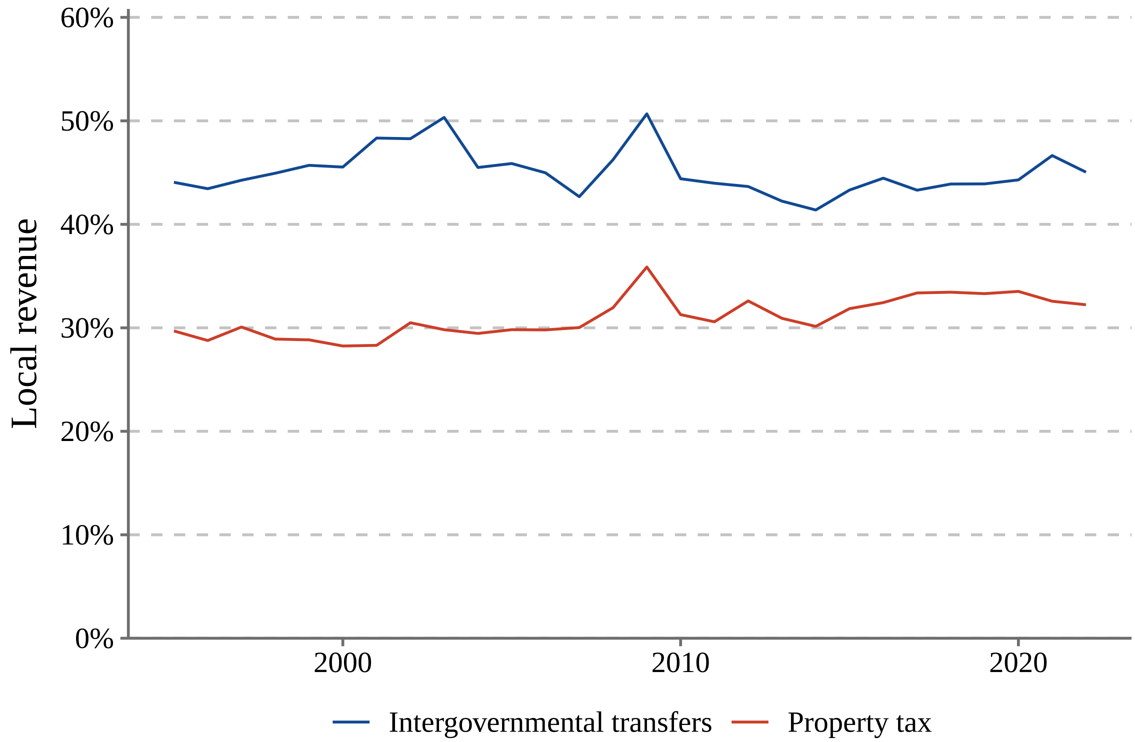
Figure 1: **Household income in 2019: HMDA vs. ACS**



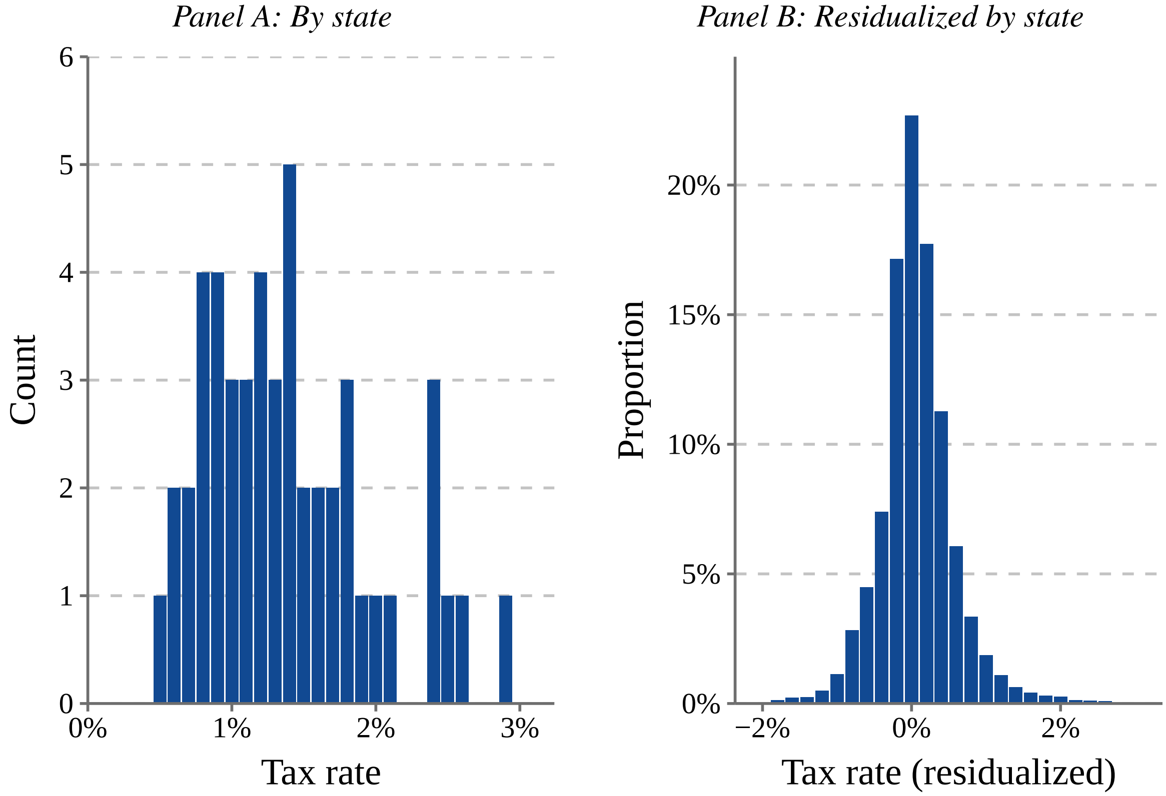
Note: This figure presents distributions of household income in 2019 across three samples: (1) the analysis sample which uses income information from the Home Mortgage Disclosure Act (HMDA), (2) the national population in the American Community Survey (ACS), and (3) homeowners who recently purchased their house with a mortgage in the ACS.

Figure 2: **Sources of local government revenue, 1970–2021**



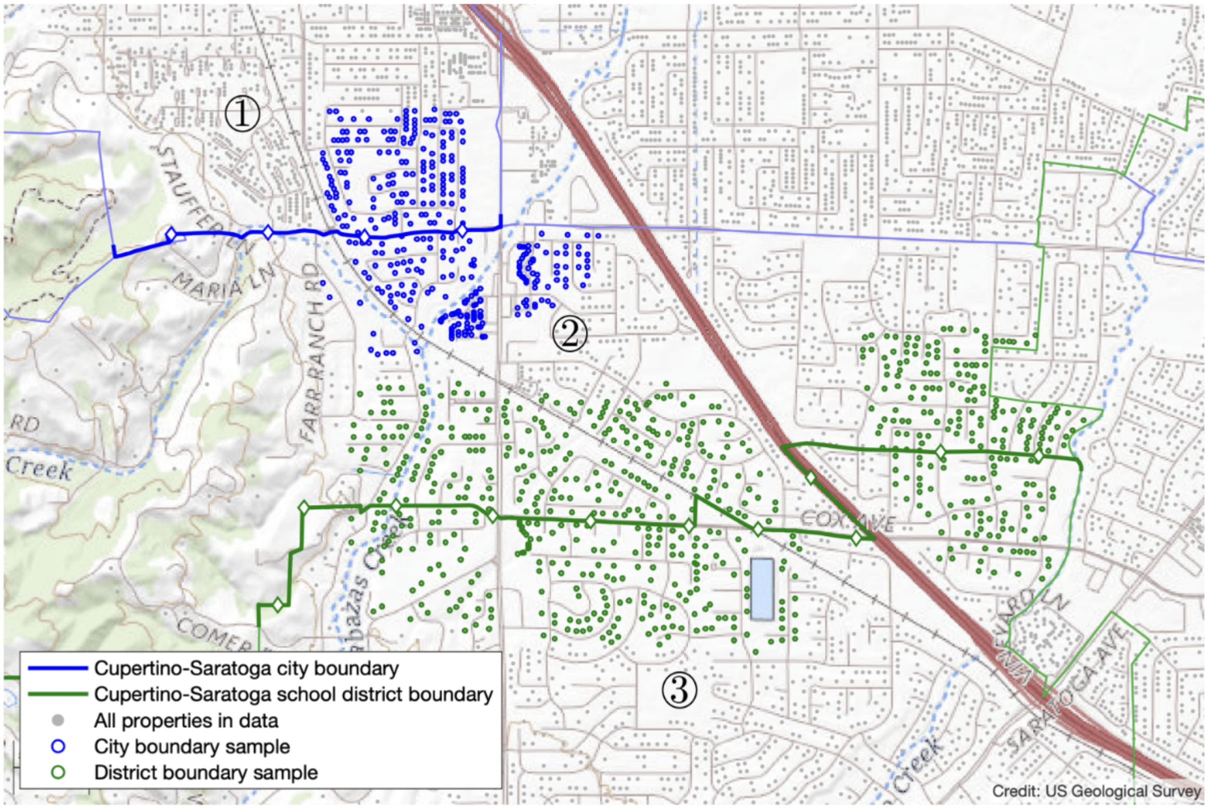
Note: This figure presents the share of local government revenue from different sources from 1970 to 2021 according to the Census of Governments.

Figure 3: **Distribution of property tax rates, 2021**



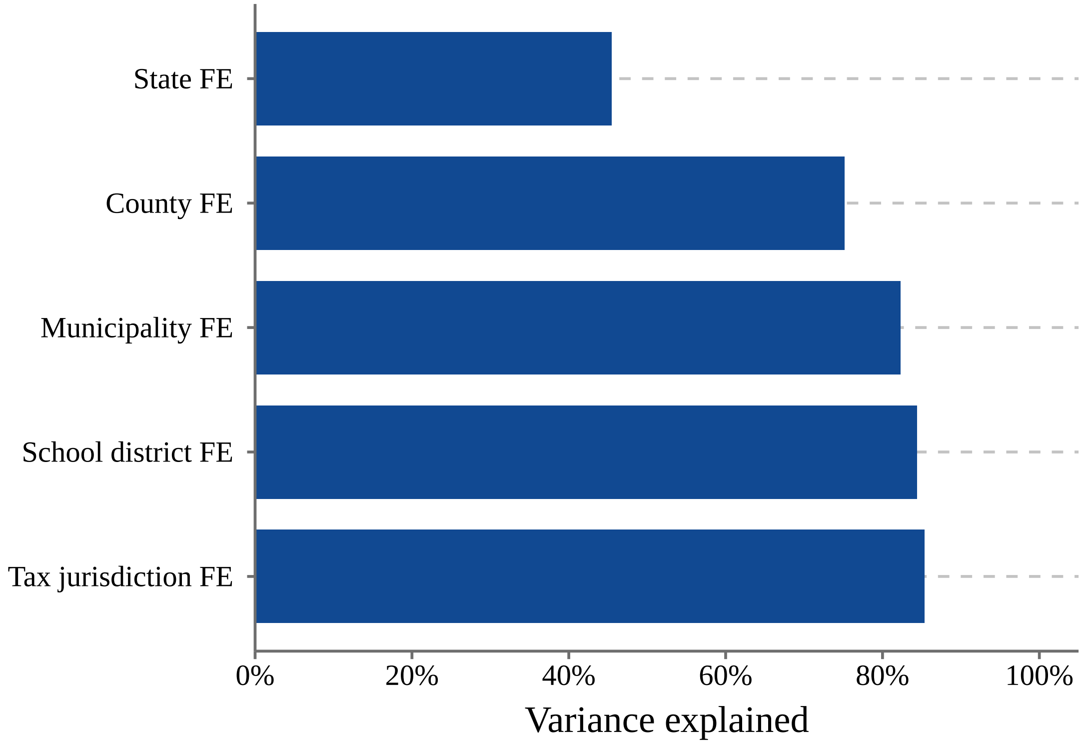
Note: Panel A of this figure presents the distribution of mean residential property tax rates aggregated at the state level. Panel B of this figure presents the distribution of residential property tax rates after residualizing by state-specific mean values.

Figure 4: Misaligned city and school district boundaries, Schönholzer (2024)



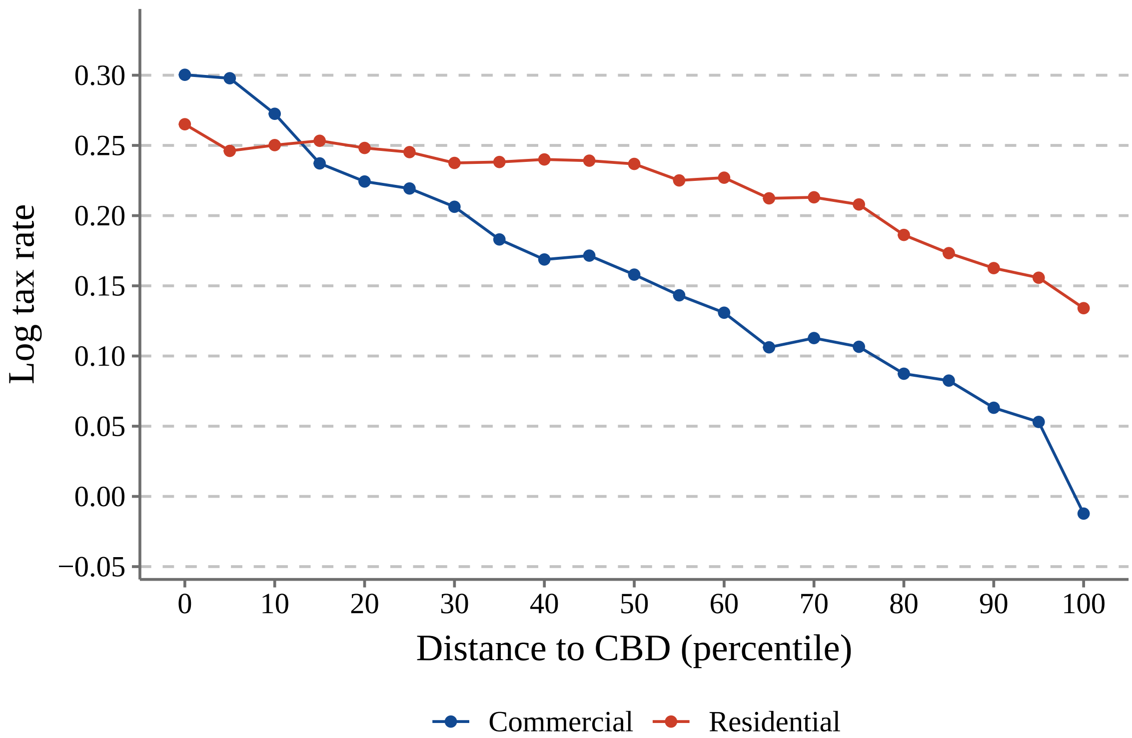
Note: This figure presents an example from Schönholzer (2024) of when municipality boundaries and school district boundaries are misaligned.

Figure 5: **Variance decomposition of residential property tax rates, 2019**



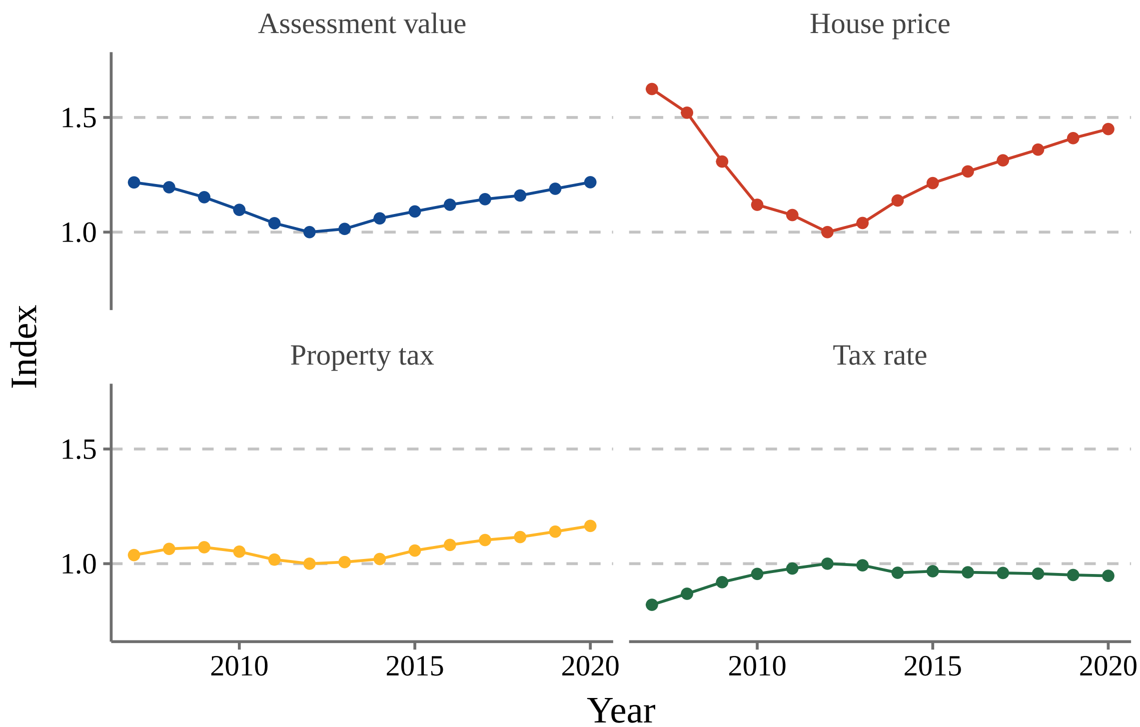
Note: This figure presents the proportion of variance in residential property tax rates explained by different levels of government. Tax jurisdiction refers to the specific combination of county, municipality, and special districts to which a parcel belongs.

Figure 6: **Binscatter of property tax rate by distance to central business district, 2021**



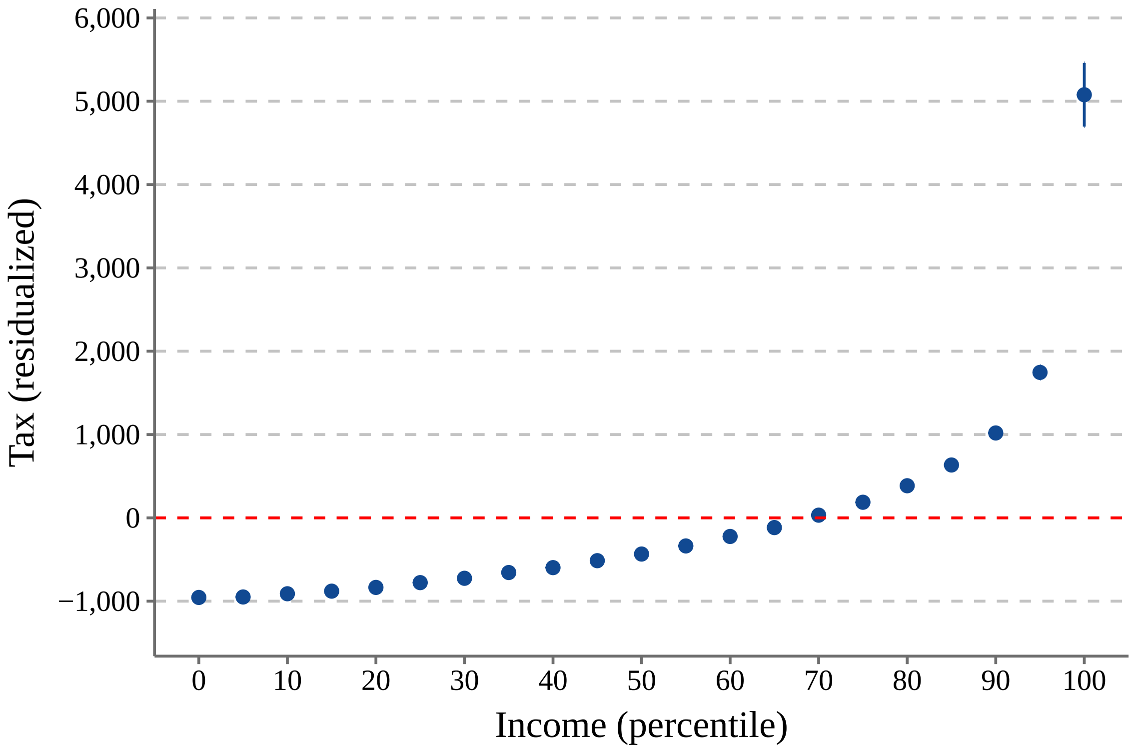
Note: This figure presents a binscatter analysis of property tax rates by percentile of distance from the nearest central business district (CBD). Percentile of distance from the nearest CBD is calculated relative to each metropolitan area, ensuring balanced representation in metropolitan areas across percentiles.

Figure 7: **House price, property value, tax rate, and property tax amount indices, 2007–2021**



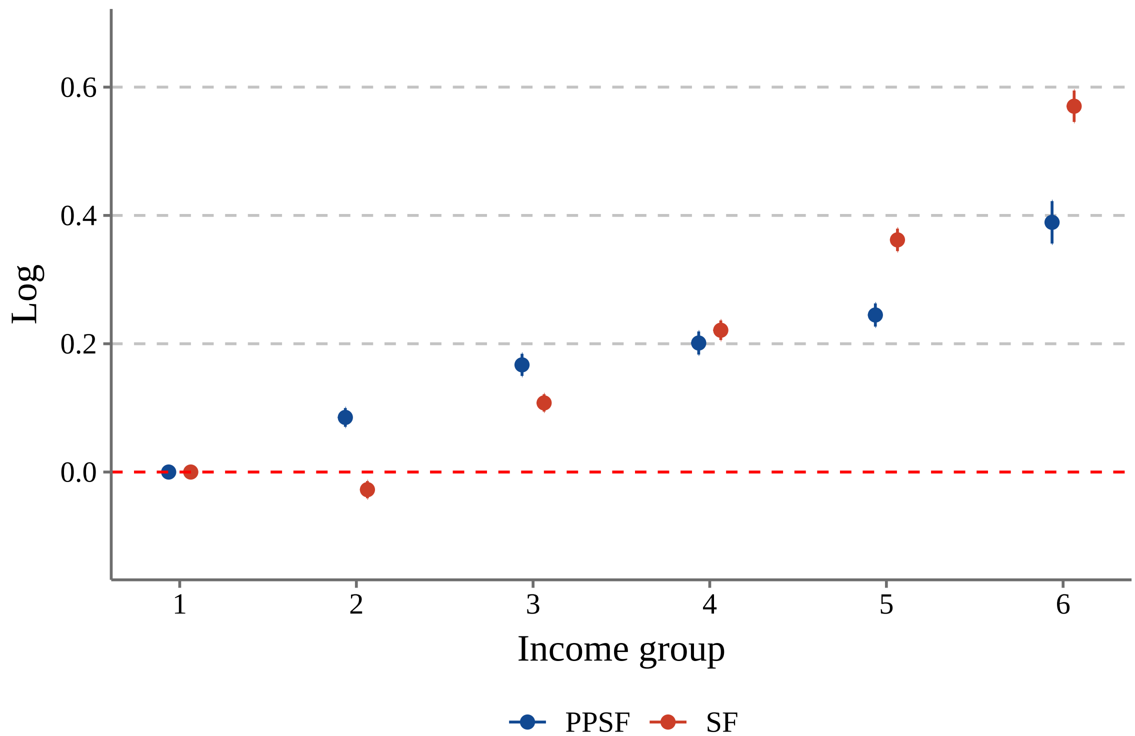
Note: This figure presents house price, property value, tax rate, and tax amount indices from 2007 to 2021. The house price index is constructed by following the repeat sales methodology from Case and Shiller (1987). To construct the property value, tax rate, and tax amount indices, I use a modified version of the repeat sales methodology, where I use repeat tax assessments instead.

Figure 8: **Nominal intrajurisdictional redistribution, 2019**



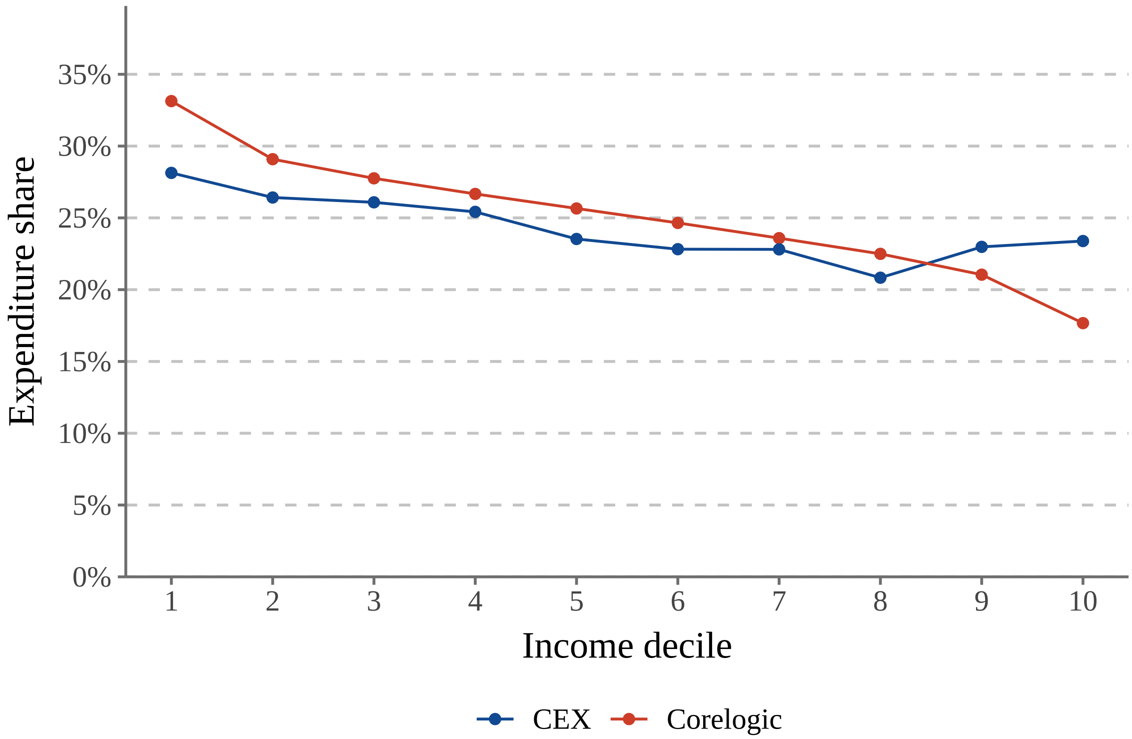
Note: This figure presents the estimated coefficients on household income percentile fixed effects for equation (1), where the outcome is property tax payment. Outcomes are ex-ante residualized by the average in the school district. Household income percentiles are defined using the national distribution of household income in the 2019 American Community Survey. Standard errors are clustered by school district.

Figure 9: **Residualized housing consumption by household income, 2019**



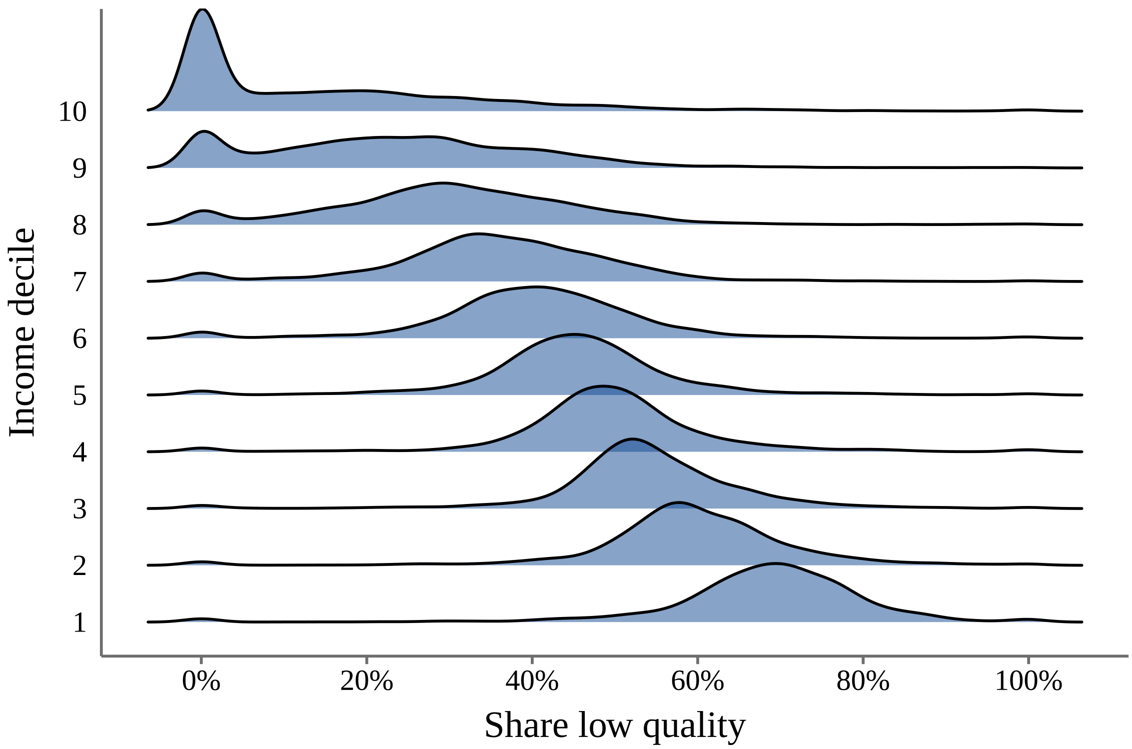
Note: This figure presents the estimated coefficients on household income group fixed effects for equation (2), where the outcomes are log house square footage and log price per square feet. Household income groups are defined as follows: (1) less than \$25,000; (2) \$25,000 to \$49,999; (3) \$50,000 to \$74,999; (4) \$75,000 to \$99,999; (4) \$100,000 to \$199,999; and (6) \$200,000 or more. Standard errors are clustered by school district.

Figure 10: **Housing expenditure shares by income group, 2019**



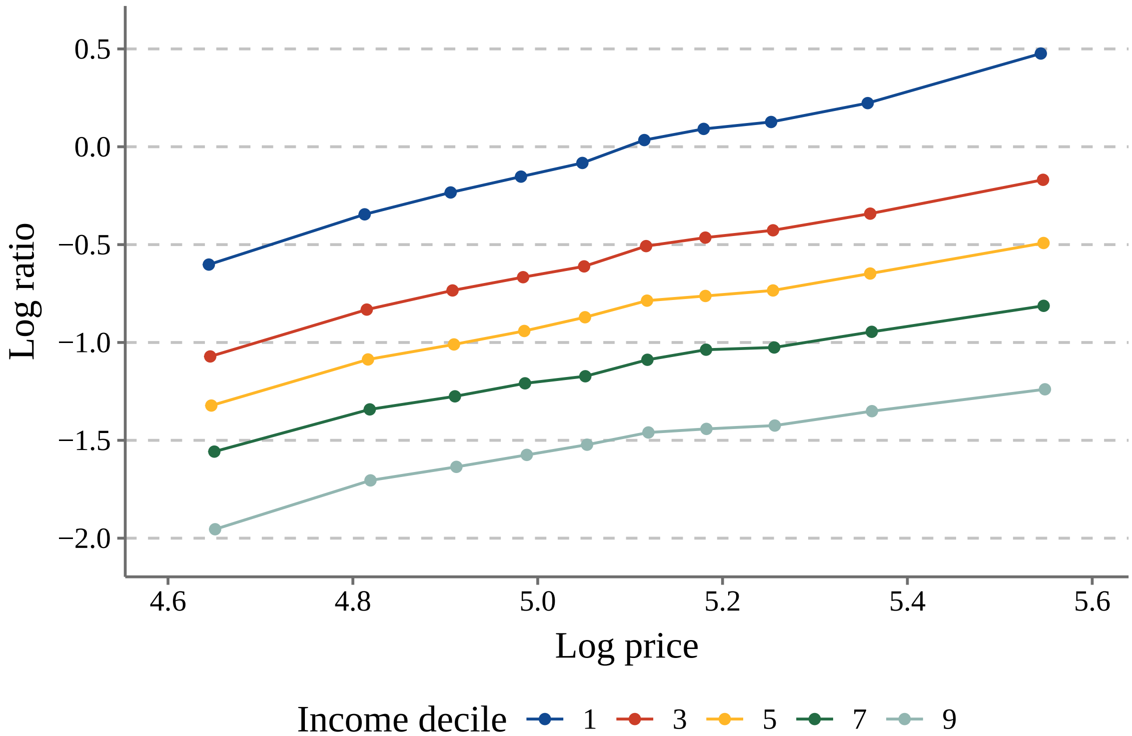
Note: This figure presents expenditure shares for housing by income group across two samples: (1) the analysis sample; and (2) the 2019 Consumer Expenditure Survey.

Figure 11: **Distribution of Cobb-Douglas parameter by income group, 2019**



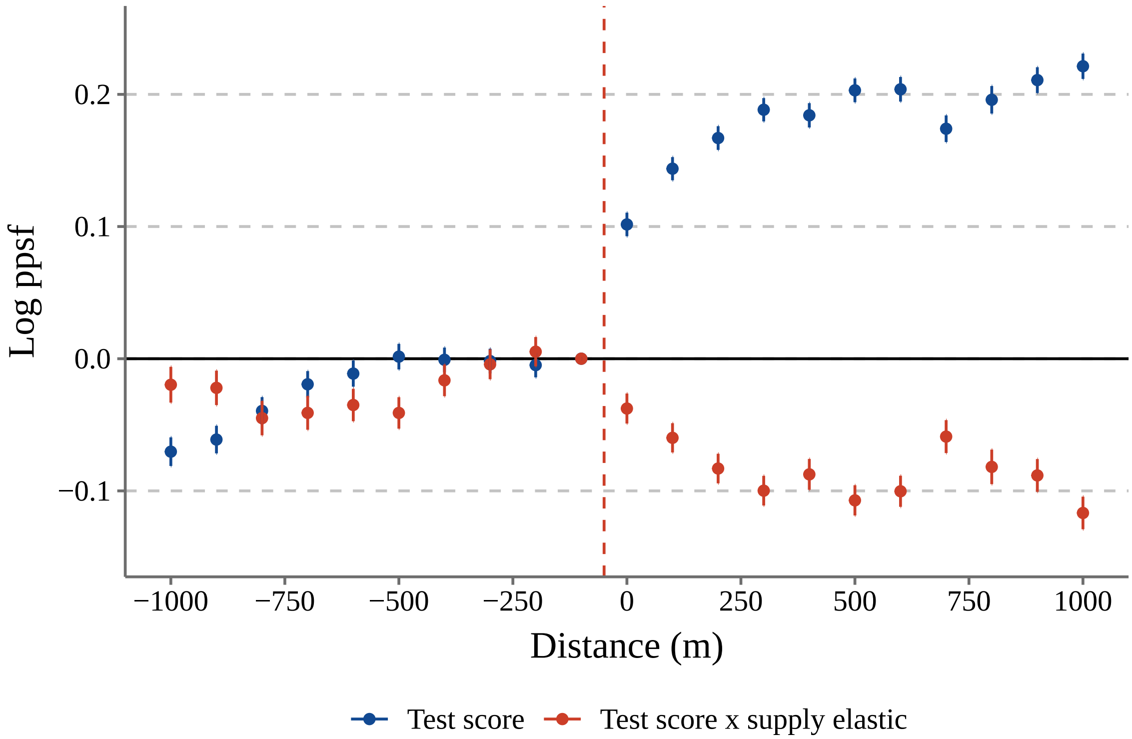
Note: This figure presents the distribution of the Cobb-Douglas parameter for the neighborhood-specific share of low-quality housing consumed by different income groups in 2019. A neighborhood is defined as a ZIP code.

Figure 12: **Binscatter of housing prices and housing expenditure share, 2019**



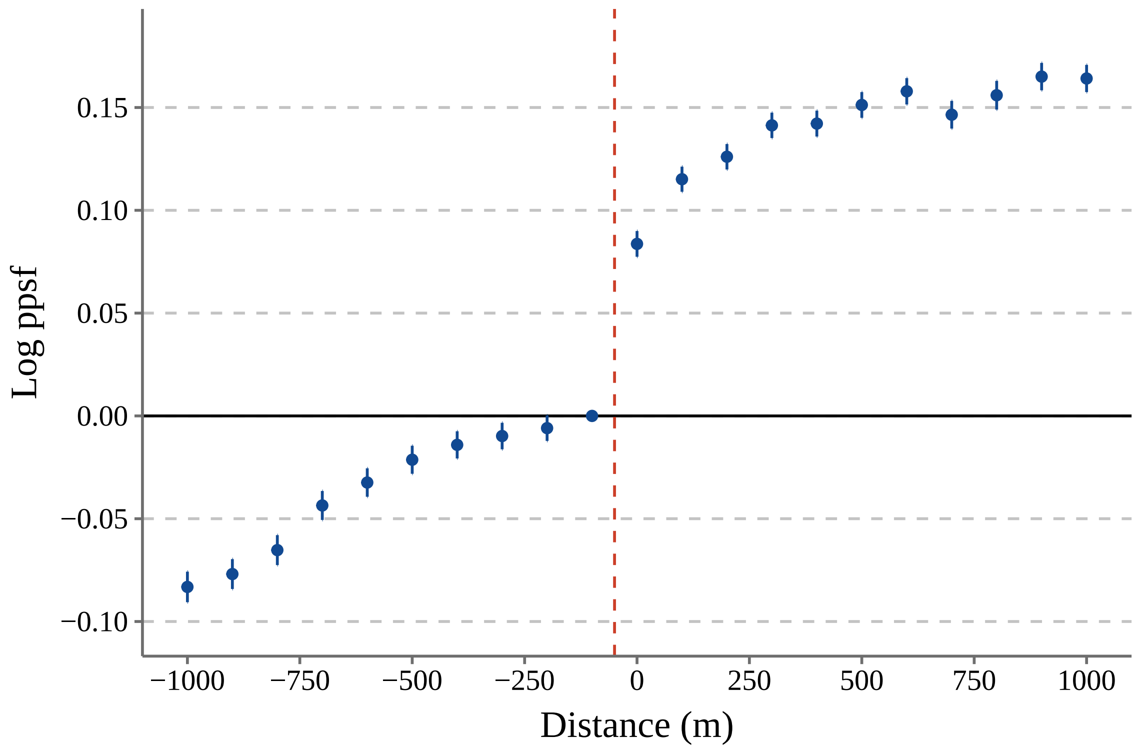
Note: This figure presents a cross-sectional binscatter of log housing prices and log housing expenditure share by income deciles. Observations are at the ZIP code-level.

Figure 13: **Border discontinuity with school district boundaries, 2019**



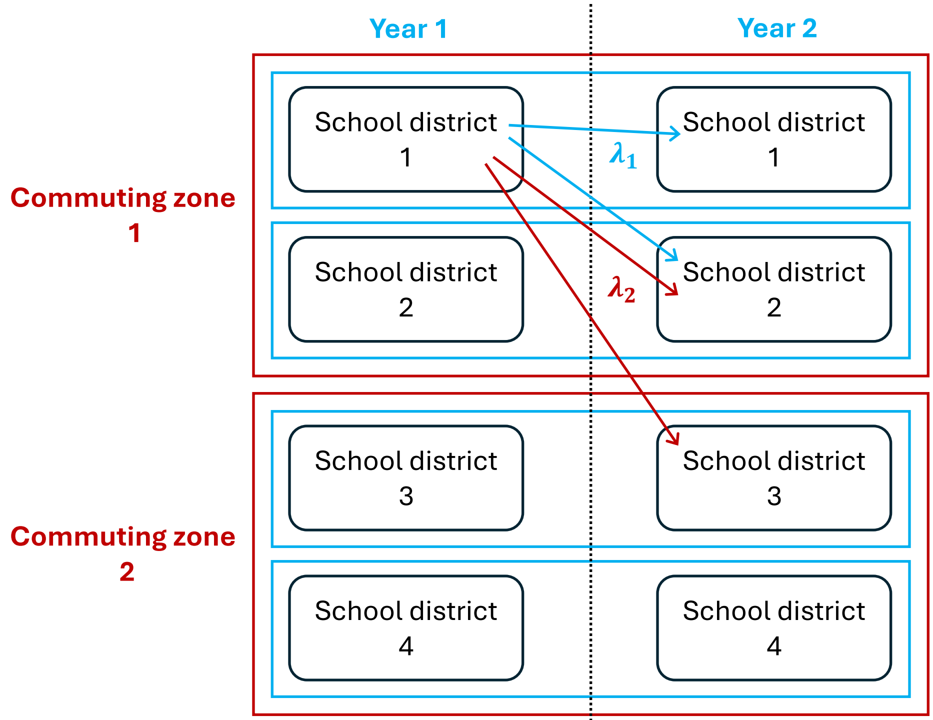
Note: This figure presents the coefficients from equation (7). Housing sales with a positive distance are located in school districts with higher test scores. Only school district boundaries located in the same municipality are included. Standard errors are clustered by school district boundary.

Figure 14: **Border discontinuity with school district boundaries, 2019**



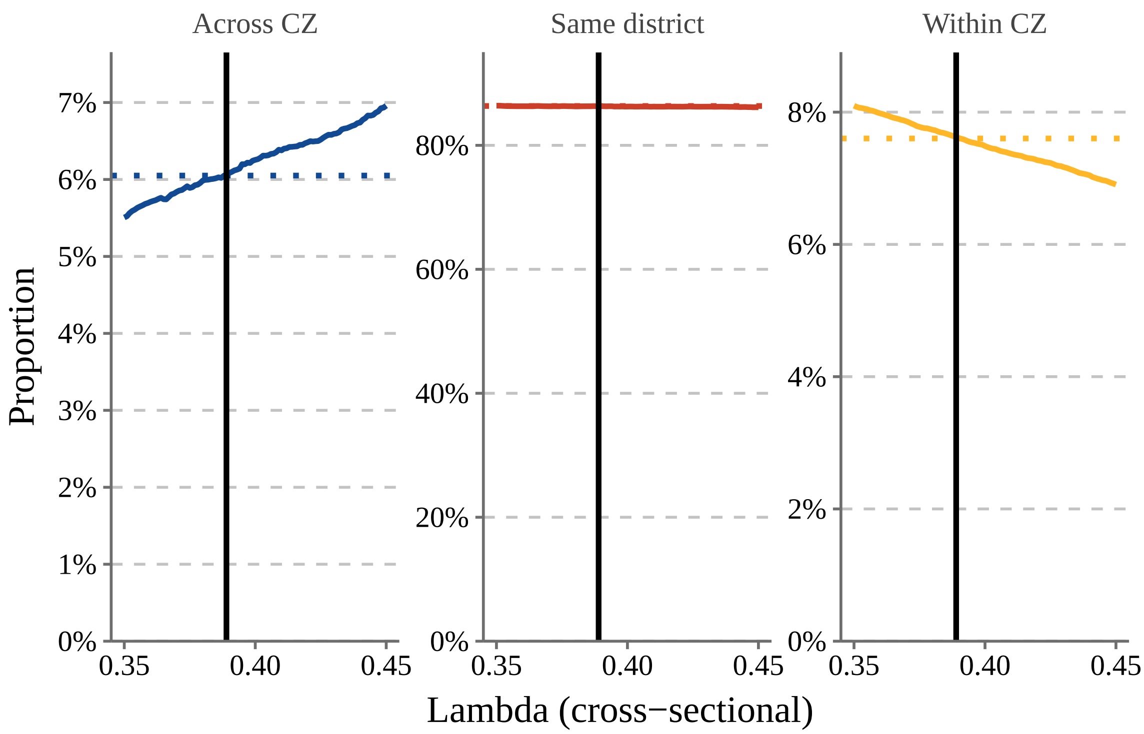
Note: This figure presents the coefficients from equation (7), without including interaction terms for housing supply elasticity. Housing sales with a positive distance are located in school districts with higher test scores. Only school district boundaries located in the same municipality are included. Standard errors are clustered by school district boundary.

Figure 15: **Nesting structure for generalized extreme value distribution**



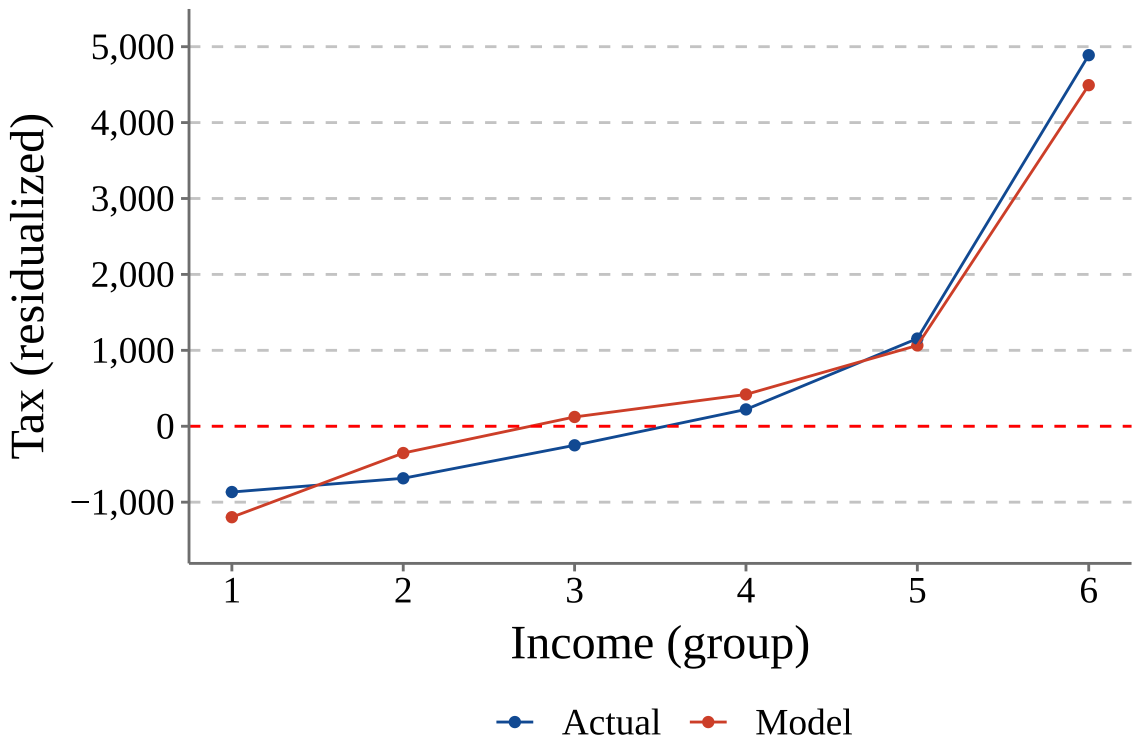
Note: This figure presents the nesting structure for household idiosyncratic preferences for school districts.

Figure 16: **Simulated versus actual migration, 2019**



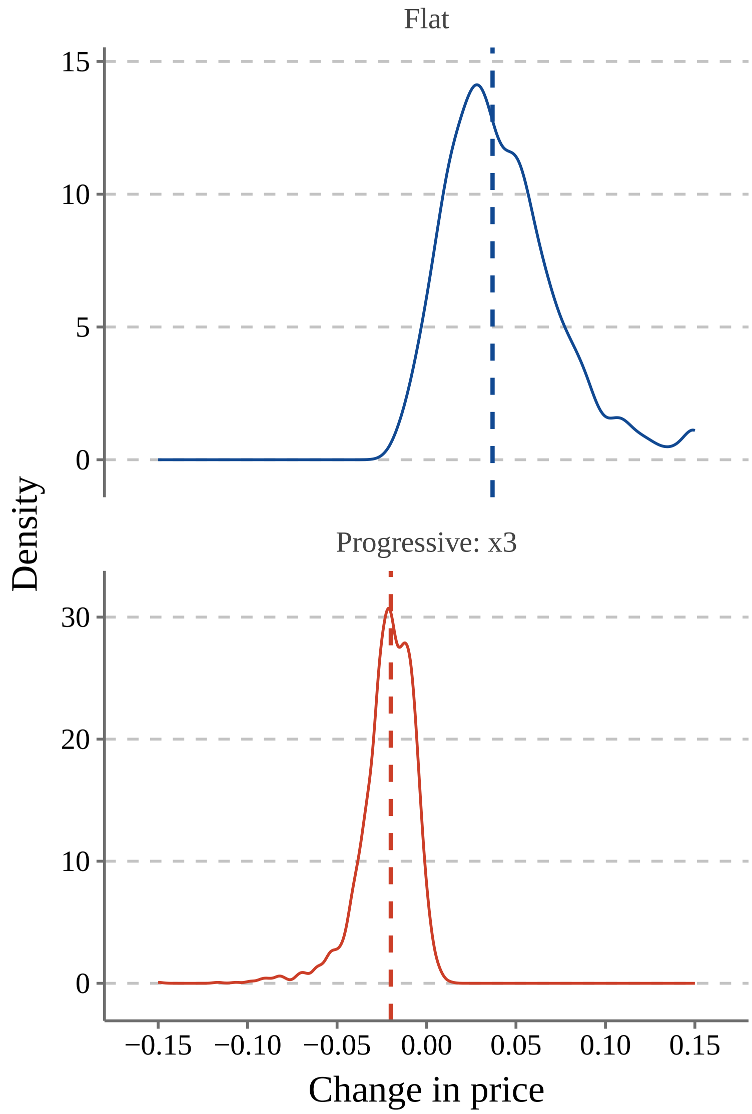
Note: This figure presents the moment equations used to identify the parameters of the generalized extreme value distribution. I fix $\lambda_1 = 0.158$ and present how gross migration shares change with λ_2. The dotted lines present the empirical moments for gross migration in the data.

Figure 17: **Model-implied nominal intrajurisdictional redistribution, 2019**



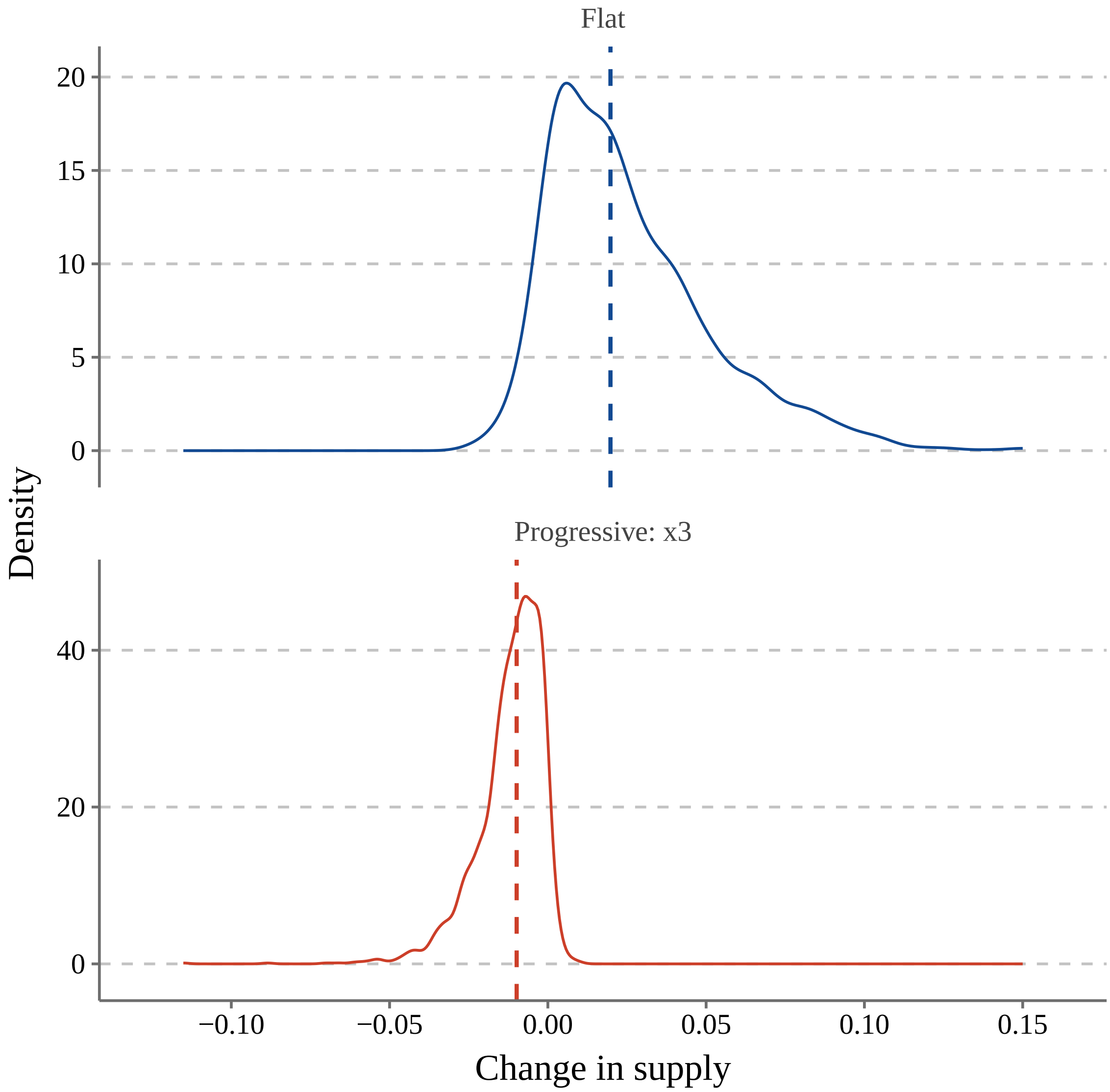
Note: This figure presents model-implied nominal intrajurisdictional redistribution by income group in 2019 using income-specific population shares from the Internal Revenue Service. Model-implied nominal intrajurisdictional redistribution is benchmarked to nominal intrajurisdictional redistribution measured using the Corelogic–HMDA data. Household income groups are defined as follows: (1) less than \$25,000; (2) \$25,000 to \$49,999; (3) \$50,000 to \$74,999; (4) \$75,000 to \$99,999; (4) \$100,000 to \$199,999; and (6) \$200,000 or more. Standard errors are clustered by school district.

Figure 18: Change in prices by school district



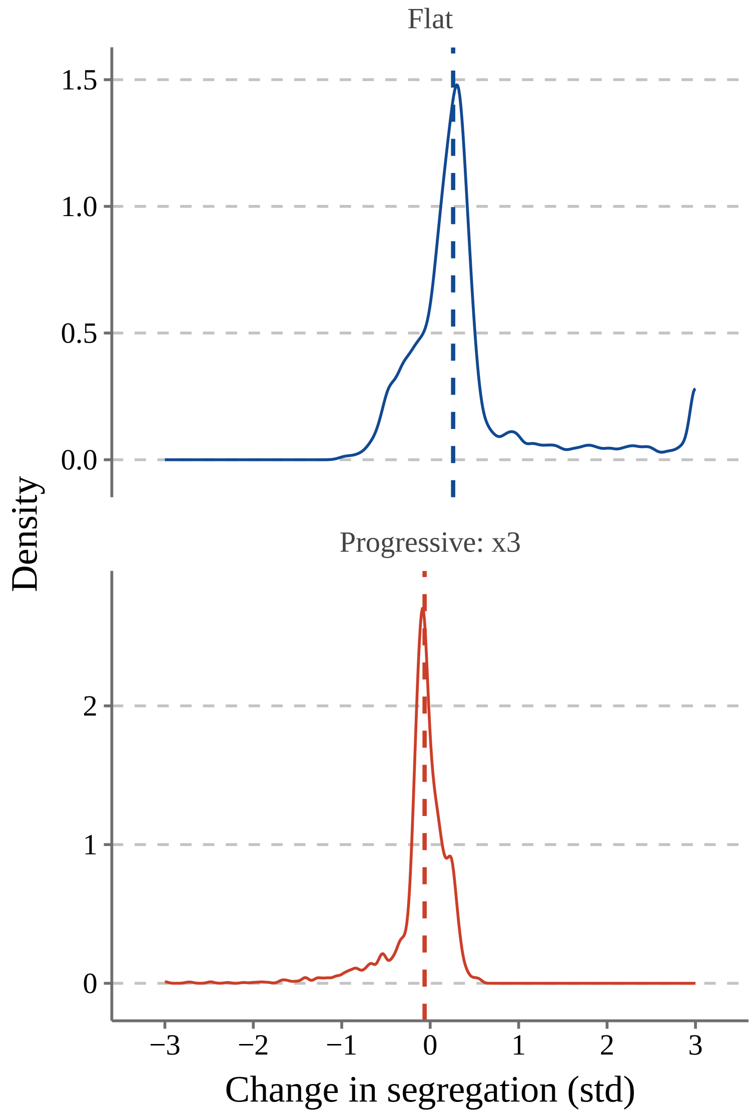
Note: This figure presents the distribution of changes in neighborhood-level average house prices switching from ad valorem property taxes to: (1) head taxes and (2) universal progressive property taxes where the marginal tax rate triples at the threshold.

Figure 19: Change in square footage by school district



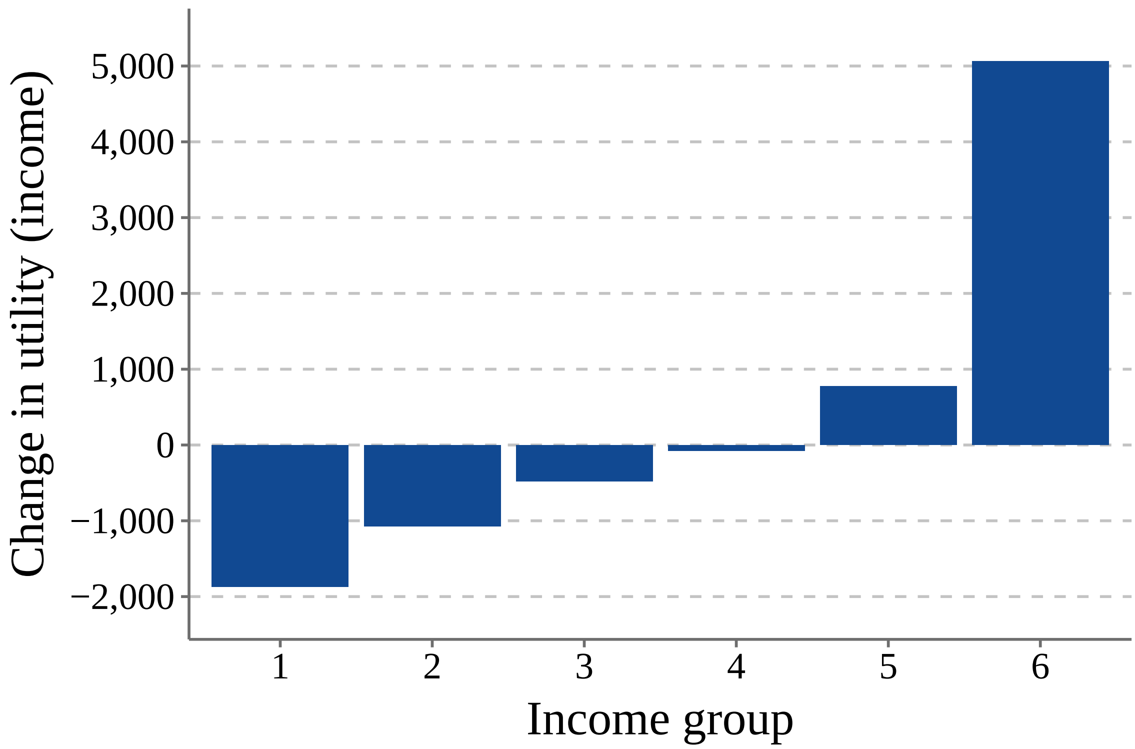
Note: This figure presents the distribution of changes in neighborhood-level total square footage switching from ad valorem property taxes to: (1) head taxes and (2) universal progressive property taxes where the marginal tax rate triples at the threshold.

Figure 20: Change in segregation by school district



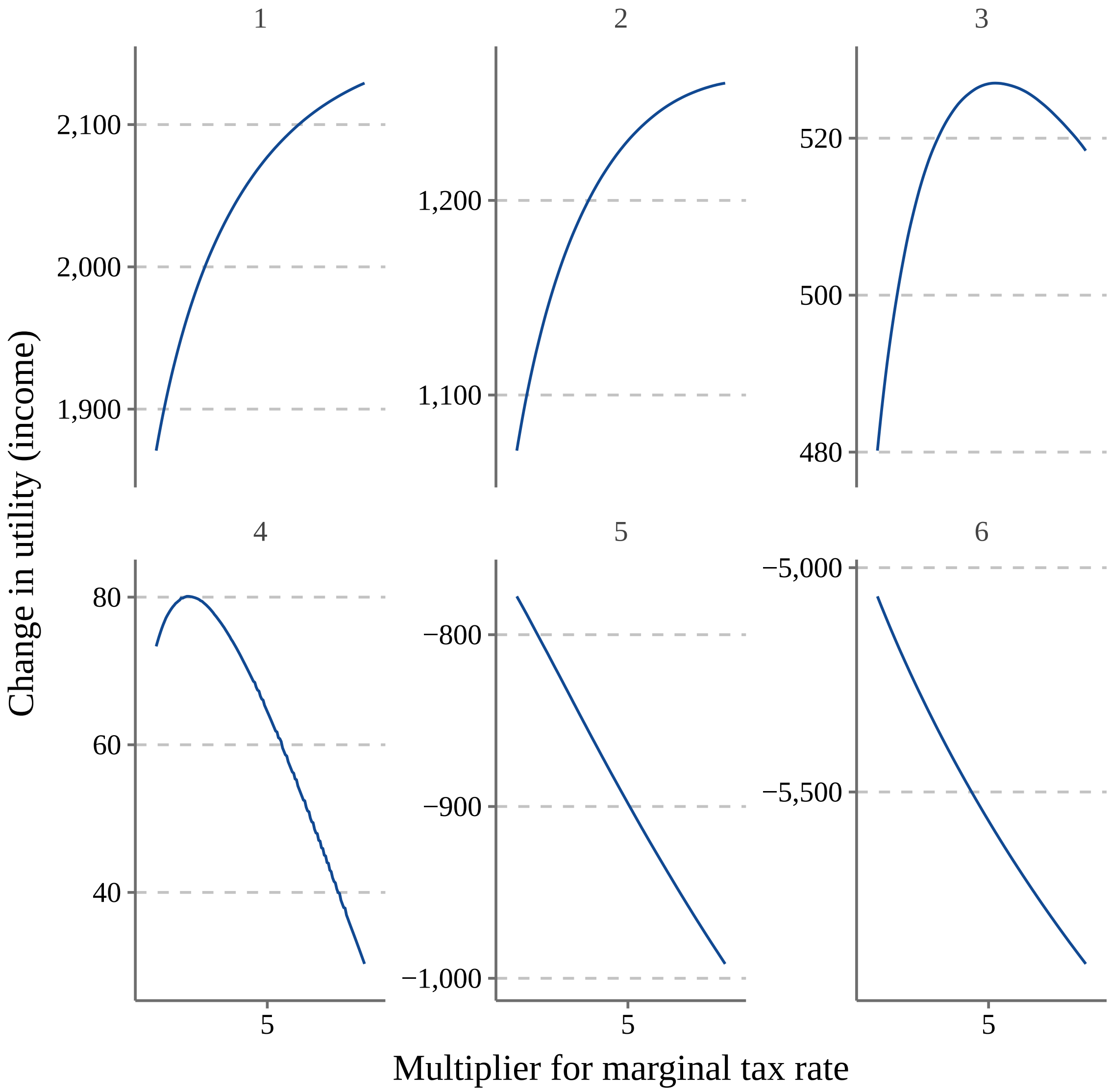
Note: This figure presents the distribution of changes in neighborhood-level segregation switching from ad valorem property taxes to: (1) head taxes and (2) universal progressive property taxes where the marginal tax rate triples at the threshold. Segregation is measured according to a dissimilarity index.

Figure 21: Welfare effect by income group, head tax



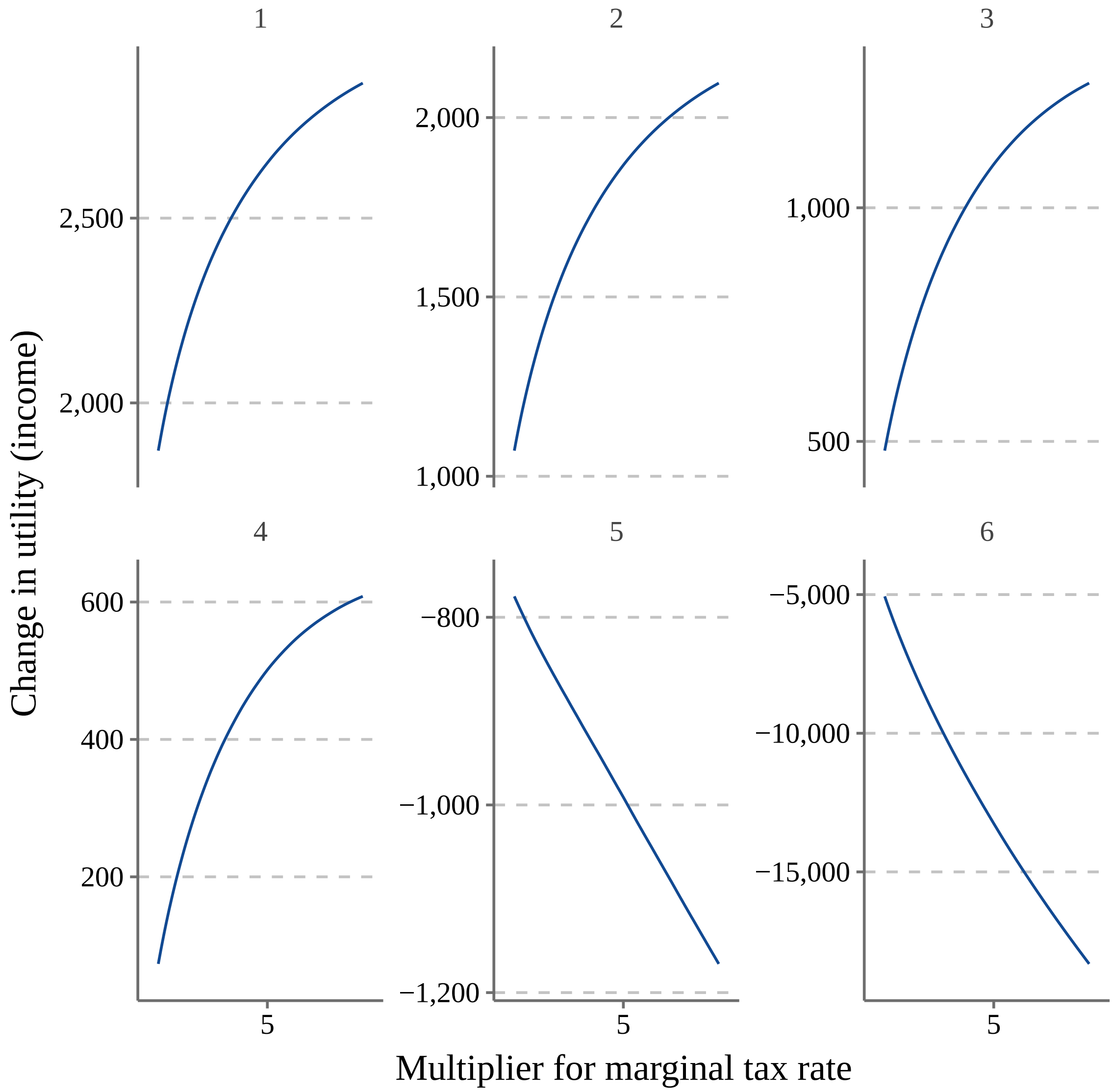
Note: Household income groups are defined as follows: (1) less than $25,000; (2) $25,000 to $49,999; (3) $50,000 to $74,999; (4) $75,000 to $99,999; (4) $100,000 to $199,999; and (6) $200,000 or more.

Figure 22: Welfare effect by income group, partial progressive tax



Note: Household income groups are defined as follows: (1) less than \$25,000; (2) \$25,000 to \$49,999; (3) \$50,000 to \$74,999; (4) \$75,000 to \$99,999; (4) \$100,000 to \$199,999; and (6) \$200,000 or more.

Figure 23: Welfare effect by income group, progressive tax



Note: Household income groups are defined as follows: (1) less than $25,000; (2) $25,000 to $49,999; (3) $50,000 to $74,999; (4) $75,000 to $99,999; (4) $100,000 to $199,999; and (6) $200,000 or more.

Table 1: **Elasticity of substitution for housing, regression estimates**

	$\log(s) - \log(1-s)$				$\log(s)$
	OLS	**IV**	**OLS**	**IV**	**IV**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
$\log r$	0.642	0.958	0.595	0.728	0.507
	(0.021)	(0.128)	(0.023)	(0.124)	(0.082)
Bartik IV		1.682		1.910	1.910
		(0.277)		(0.323)	(0.323)
F-stat		567.6		693.5	693.5
Income FE	X	X	X	X	X
Commuting zone FE	X	X			
County FE			X	X	X

Table 2: **Outmigration elasticity, regression estimates**

	Coef.	Std. err.
β	0.035	0.003
σ^{-1}	0.191	2.891