The Welfare Effects of Local Property Taxation*

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Abstract

In the United States, property taxes are ubiquitous despite their distortionary effects. This paper develops a spatial equilibrium model to quantify the welfare effects of local property taxation. I use household microdata to estimate housing demand: the price elasticity of housing expenditures is 0.51, rejecting a common assumption of unit elastic demand. Counterfactual simulations show that switching from property taxes to a non-distortionary tax 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. Increasing redistribution with 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 median effective tax rates ranging from a minimum of 0.3% in Hawaii to a maximum of 2.7% in New York. Intrastate variation in tax rates reflects 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 local 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 elasticity of housing expenditure with respect to price is 0.51 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 total expenditure. Furthermore, I estimate that households have an outmigration elasticity of 9.2 with respect to income. 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] Coun-

[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 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. Residential property is taxed at 0.85% of its value up to $2,500,000

terfactual simulations reveal important tradeoffs between equity and efficiency. Compared to head 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 examined 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 using household revealed preferences.

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.

and 1% of the value exceeding \$2,500,000.

[4]In Denmark, residential 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.

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; 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.[5] If the transaction is associated with a mortgage,

[5] A parcel is a distinct, legally defined piece of real estate property. A property's parcel number is a unique identifier assigned by thecounty assessor's office.

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.

The Corelogic Historical Property Taxation 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. I restrict my analysis sample to counties with: (1) transaction and tax assessment records dating back to at least 2010; and (2) a minimum of 1,000 transactions from 2010 to 2019. Counties in my sample include 94% percent of the U.S. population. Appendix Figure A.9 provides a map of the counties in my sample, and Appendix Table A.1 provides sample statistics on the counties. When simulating household welfare under alternative tax regimes, I further 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.[6]

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 property 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.[7]

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.[8] 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.

[6]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.

[7]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.

[8]Household income reflects pre-tax income amounts reported on mortgage applications. Mortgage lenders will typically verify an applicant's income by requesting paycheck stubs and tax returns.

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 mortgages 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 C explains the algorithm in detail and provides summary statistics on the merging process. As the Bayer et al. (2022) 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 55% 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 empirical analysis, provided that unmatched mortgages are not systematically different from matched mortgages. I find that the distribution of loan amounts is similar for matched mortgages and unmatched mortgages (Appendix Figure A.10), except that unmatched mortgages are more likely to have outlier loan amounts, partially explaining why they remain unmatched.

2.3 Supplementary data

To further facilitate my analysis of housing consumption and property taxation in the U.S., I compile fiscal, demographic, employment, and price data at various geographical levels from multiple supplementary datasets.

Fiscal. For fiscal data, I use the Census of Government, the National Center for Educational Statistics, and the Stanford Education Data Archive. The Census of Governments, an annual survey of local and state governments on revenue and expenditure, has been conducted by the U.S. Census Bureau since 1970. The National Center for Education Statistics is a database of enrollment and financial measures for U.S. school districts since 1987. The Stanford Education Data Archive is a database of standardized test outcomes for school districts in the U.S from 2009 to 2019.

Demographic. For demographic data, I use the Consumer Expenditure Survey, the Individual Income Tax Statistics, the American Community Survey, and Infutor Data Solutions. The Consumer Expenditure Survey is a quarterly interview of household expenditure conducted by the U.S. Bureau of Labor Statistics since 1980. The Individual Income Tax Statistics is a tabulation of U.S. individual income tax returns: it provides ZIP code-level income distributions since 1990. The American Community Survey has been annually conducted by the U.S. Census Bureau since 2005 and collects socioeconomic data from approximately 1% of the U.S. population.[9] Infutor

[9] In particular, I use the Supplementary Poverty Measure, which combines pre-tax household income from the America Community Survey with the TAXSIM calculator from the National Bureau of Economic Research to measure post-tax household resources.

Data Solutions is a database that records the entire address history for more than 300 million U.S. residents.[10]

Employment. For employment data, I use the 2000 U.S. Census of Population, the Quarterly Census of Employment and Wages, and Card, Rothstein, and Yi (2025). I use journey to work and place of work tabulations from the 2000 U.S. Census of Population, which measure household commuting flows at the census tract level. The Quarterly Census of Employment and Wages reports quarterly measures of U.S. employment and wages by industry at a county level and has been conducted by the U.S. Bureau of Labor Statistics since 1980. Card, Rothstein, and Yi (2025) provides causal estimates for the effects of location on earnings.

Price. For price data, I use Zillows Housing Data, the Nielsen Homescan Panel, and Baum-Snow and Han (2024). Zillow Housing Data provides typical home values and market rents for U.S. ZIP codes.[11] Launched in 2004, the Nielsen Homescan Panel is a nationally representative longitudinal survey in which participating U.S. households record their purchases of groceries and consumer packaged goods (e.g., snacks and personal care products). Baum-Snow and Han (2024) provides causal estimates of housing supply elasticities for census tracts.

Appendix D provides a detailed explanation on how the supplementary datasets are used.

2.4 Validating household income

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 my CoreLogic-HMDA sample. 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.[12]

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

[10]Infutor is a data aggregator of address data using many sources including phone books, magazine subscriptions, and credit header files. This data was first described and made use of by Diamond, McQuade, and Qian (2019) to study household migration.

[11]Typical home values and market rents are provided for different housing types (e.g., single-family versus condos) and housing quality (e.g., homes in the 5th to 35th percentile range versus homes in the 65th to 95th percentile range).

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

that the income measures in the HMDA data are reliable.[13] 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 2019 ACS. This reweighting ensures that my empirical analysis is representative of the national population.

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.[14]

Property taxes are levied annually based on three factors: a parcel's property tax rate, property value, and assessment ratio. 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.[15] Assessment ratios, typically established by

[13] Mortgage lenders will typically verify an applicant's income and employment by requesting documents such as paycheck stubs, tax returns, and bank statements.

[14] 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.

[15] Assessor offices typically use prior sale transactions to predict the market value of all properties. Historically, predicted market values have generally aligned with sale prices from transactions. Appendix Figure A.1 plots the median property value to sale price ratio from 2007 to 2020. Ratios are calculated using property values from the current year and sale prices from the previous year, since property values are restrospective; e.g., ratios in 2007 are calculated using property values from 2007 and sale prices from 2006.

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%. I use effective property tax rates to present stylized facts about local property taxation.

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 median 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 median values, thereby isolating within-state variation.[16] States differ widely in their reliance on property taxes, with median residential property tax rates ranging from a minimum of 0.3% in Hawaii to a maximum of 2.7% in New York.

Substantial intrastate variation in property tax rates reflects 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.[17] In practice, K-12 school districts generally characterize the smallest unit of local government and receive a majority of the property taxes collected in a tax jurisdiction.[18] 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

[16] Appendix Figure A.2 presents interstate and intrastate distributions of commercial property tax rates.

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

[18] 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.

and calculate the variance in property tax rates explained by each level. That is, I estimate a series of regression equations:

$$y_i = \lambda_{g_i} + \varepsilon_i$$

where y_i is the property tax rate for residential parcel i in 2019 and λ_{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.[19] 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.[20] 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 residential property tax rates with percentile of distance from the nearest central business district.[21] 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 for a given parcel remained stable. In practice, local governments raise property tax rates when property values decline and decrease rates when values rise.[22] Local governments typically hold legislative sessions where legislators use anticipated property values provided by county assessor's

[19] Appendix Figure A.3 repeats the same variance decomposition exercise, but for commercial parcels.

[20] 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.

[21] I define as a central business district the collection of census tracts categorized as business districts in the 1982 Census of Retail Trade. Results are qualitatively similar using alternative definitions of central business districts (e.g., location of city halls).

[22] 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.

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 λ_{w_i} are household income percentile fixed effects.[23] 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, γ_{s_i} are school district fixed effects, and λ_{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 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.

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

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.[24]

4.1 Housing demand

Assume a unit measure of heterogeneous households, where households differ according to their type θ.[25] 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:

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

Notably, households have heterogeneous preferences for housing variety. The parameter $\delta_{\theta j}$ governs neighborhood-specific *taste* of type θ households for low-quality versus high-quality

[24] For expositional simplicity, the model described in this section assumes local governments use some combination of ad valorem taxes and head taxes. An extension of the model allowing for governments to use non-linear taxes is described in Appendix F.

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

housing consumption. The parameters $\alpha_\theta \alpha_j$ govern the neighborhood-specific *appeal* of housing relative to non-housing consumption for type θ households.[26] 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:

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

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.

4.3 Labor

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

[26] I assume log-additive separability by type in the neighborhood-specific appeal of housing; i.e., $\log\left(\alpha_{\theta j}\right) = \log\left(\alpha_\theta\right) + \log\left(\alpha_j\right)$. I directly test and fail to reject this assumption in the data: Figure 13 provides descriptive evidence validating the assumption.

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

Firms in neighborhood j produce a tradable intermediate good with a constant returns to scale production function:

$$F\left(K_j, B_j L_j\right) = B_j L_j f\left(\frac{K_j}{B_j L_j}\right)$$

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:

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

The marginal product of labor is then:

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

Assume free entry of firms, meaning wages equal the marginal product of labor:

$$w_{\theta j} = B_j R(\rho)\theta$$

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.[27] 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.[28]

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.

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

[28] Gómez-Reino, Lago-Peñas, and Martinez-Vazquez (2023) conducts a meta-analysis and finds inconclusive evidence on the existence of economies of scale in the production of local public services.

An equilibrium is defined by (1) market-clearing in the housing market:

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

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

$$T_j + \sum_{\theta} \frac{N_{\theta j}}{\sum_{\theta} N_{\theta j}} \left(h^*_{\theta L j} r_{Lj} + h^*_{\theta H j} r_{Hj} \right) \tau_j = MC_j$$

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 the amount of housing consumed by households (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; that is, parameters that govern housing consumption conditional on households choosing to live in a given neighborhood.

Rent imputation. Because I use property 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 using price-to-rent ratios. 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 annual metropolitan area-level price-to-rent ratios using Zillow Housing Data on median prices and rents for single-family homes. For each metropolitan area and year, I divide median prices for single-family homes by median rents for single-family homes to get a price-to-rent ratio.[29] I then use my imputed owners' equivalent rent from house prices to estimate housing expenditure shares by income group. As a validation exercise, I benchmark housing expenditure shares calculated using transactions in 2019 to the 2019 Consumer Expenditure Survey and find relatively similar shares by income (Figure 10).

Housing taste. 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, the parameter $\delta_{\theta j}$ is identified by a household's respective consumption of each housing variety. 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 housing varieties, 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. If households of type θ were to consume housing priced at an average of \$6 per square feet, it must be the case that such households spend 80% of their housing expenditure on low-quality housing and 20% on high-quality housing. Therefore, I would estimate a taste parameter of $\delta_{\theta j} = 0.2$ for households of type θ in neighborhood j. Notably, identifying $\delta_{\theta j}$ requires ex-ante defining low- versus high-quality housing, where the choice of definition is a scale normalization due to the linear nature of the problem.

I estimate annual neighborhood-level taste parameters using property tax assessments, where neighborhood is defined as a ZIP code. I use property value as a proxy for price: low- and high-quality housing in a neighborhood is defined as the average property value per square feet in the bottom and top tercile of property value per square feet, respectively.[30] Figure 11 presents the distribution of $\delta_{\theta j}$ by ZIP code that I estimate for each income group in 2019. I find that higher

[29] Housing prices and rents in the Zillow Housing Data imply a national price-to-rent ratio of 12.6 in 2019, consistent with price-to-rent ratios estimated in Diamond and Diamond (2024).

[30] I use property tax assessments instead of property transactions since property tax assessments are comprehensive, meaning that definitions of low- and high-quality housing are absolute and comparable over time. In the majority of states, property values are legally mandated to reflect how much the property would sell for in an open market. Assessor offices use prior sales transactions to predict market values for all properties (Appendix Figure A.1).

income groups are monotonically more likely to consume high-quality housing, consistent with intuition that rich households live in more desirable houses.

I then calculate income-specific rent indices $\tilde{r}_{\theta j}$ for 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 Housing Data, which provides ZIP code-level price indices for the bottom tercile and top tercile of housing:[31]

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

Elasticity of substitution. Next, I estimate the parameter η, which determines the elasticity of subsitution between housing and non-housing consumption. The parameter η crucially governs the intensive margin of housing demand, as it governs how households adjust their housing expenditure in response to prices. Suppose that we observe housing expenditure share $S_{\theta j}$ for income group θ in neighborhood j in two periods t and $t+1$. Through the lens of my model in Section 4, the change in housing expenditure share from period t to $t+1$ is given by:

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

where $\tilde{r}_{\theta j}$ 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 appeal of housing, and α_j is neighborhood-specific appeal of 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 $S_{\theta j}$ from transactions and rental tax rates τ_j from tax assessments 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.[32] 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 appeal of housing with income decile fixed effects.[33] Therefore, I etimate the parameter η using a combination of

[31] The Zillow Housing Data provides ZIP code-level price indices for homes in the 5th to 35th percentile range versus homes in the 65th to 95th percentile range.

[32] Appendix D 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.

[33] 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.

cross-sectional and longitudinal variation in housing expenditure shares.

A naive regression of equation (4) produces a biased estimate of the parameter η, due to the standard price endogeneity concern that prices may be correlated with unobserved quality; i.e., changes in rents $\Delta \log\left(\tilde{r}_{\theta j}\right)$ are correlated with changes in the appeal of housing $\Delta \log\left(\alpha_j\right)$. For example, neighborhoods with higher housing prices may also have more modern, and thus more desirable, houses. Figure 12 presents a binscatter correlating changes in log housing expenditure shares with changes in log housing prices from 2010 to 2019. Without price endogeneity, the estimated slope from a least squares regression would identify the parameter η.[34]

To address price endogeneity, I instrument for changes in rent prices with ZIP-code level Bartik labor demand shocks $Bartik_j$.[35] I make the identification assumption that local labor demand shocks are uncorrelated with changes in neighborhood-specific appeal of 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 appealing relative to non-housing consumption.

The fact that local labor demand shocks may increase income is not an exogeneity violation, since I directly observe income and control for non-homothetic preferences for housing with income decile fixed effects. A violation of my identification assumption would instead, for instance, be 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 appealing relative to non-housing in neighborhoods with a large tech industry.[36]

[34] Appendix Figure A.4 presents a binscatter correlating changes in log housing expenditure shares with changes in log housing prices by income group from 2010 to 2019. Estimated slopes from a least squares regression are similar across income groups, confirming homogeneity in the parameter η across income groups.

[35] I construct the Bartik labor demand shocks in a similar fashion as Baum-Snow and Han (2024). In particular, I interact ZIP code level industry employment shares in 2000–from the 2000 U.S. Census of Population–with national changes in employment by industry from 2010 to 2019–from the Quarterly Census of Employment and Wages. Industry is defined at a 2-digit NAICS code.

[36] One concern is that local labor demand shocks improve the quality of housing relative to non-housing through new construction and renovations. I do not find evidence of this, likely due to construction activity being stagnant in the U.S. since 2007.

Therefore, my estimating equation is:

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

where $S_{\theta j}$ is the average housing expenditure share for households of income decile θ in ZIP code j, $\tilde{r}_{\theta j}$ is the rent index for housing, τ_j is the rental tax rate, p_j is the price of non-housing consumption, $Bartik_j$ is a ZIP code-level Bartik instrument, λ_θ are income decile fixed effects, and γ_{c_j} are county fixed effects. I weight ZIP codes by their population in the 2010 Decennial Census, and cluster standard errors by ZIP code.

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.[37] Notably, my elasticity estimates are similar in magnitude to previous estimates in the literature.[38]

Housing appeal. 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. Suppose that we observe housing expenditure share $S_{\theta j}$ for income group θ in neighborhood j. From my model in Section 4, housing expenditure share is given by:

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

where $\tilde{r}_{\theta j}$ 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 appeal of housing, and α_j is neighborhood-specific appeal of housing. Therefore, when the parameter η is known, the appeal parameters are directly invertible

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

[38] To my best knowledge, Albouy, Ehrlich, and Liu (2016), with an estimate of 0.6 for the elasticity of housing expenditure share with respect to price, is the only prior work to estimate such an elasticity in the U.S. context. Albouy, Ehrlich, and Liu (2016) estimates the elasticity using cross-sectional differences in housing expenditure shares without instrumenting for housing prices.

from housing expenditure shares. My estimating equation is thus:

$$\log\left(\frac{S_{\theta j}}{1-S_{\theta j}}\right) = (1-\eta)\log\left(\tilde{r}_{\theta j}\left(1+\tau_j\right)\right) + \gamma_j + \lambda_\theta + \varepsilon'_{\theta j} \tag{6}$$

where $S_{\theta j}$ is the average housing expenditure share for households of income decile θ in ZIP code j, $\tilde{r}_{\theta j}$ is the rent index for housing, τ_j is the rental tax rate, γ_j are ZIP code fixed effects, and λ_θ are income decile fixed effects. Income decile fixed effects identify $\eta \log(\alpha_\theta)$, whereas ZIP code fixed effects identify $(1-\eta)\log\left(p_j\right) + \eta \log\left(\alpha_j\right)$.[39] To bring the reduced form equation (6) to data, I set $\eta = 0.27$ as estimated in Table 1.

Figure 13 presents a cross-sectional binscatter correlating log housing expenditure shares with log housing prices by income group in 2019. Suppose we were to fit a least squares regression for each income group. Intuitively, differences in the intercept by income group identify parameter α_θ, whereas average deviations from a slope of $(1-\eta)$ identify parameter α_j. I find that 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.

5.2 Extensive margin of housing demand

I proceed to estimate parameters that govern the extensive margin of housing demand; that is, parameters that govern how households choose which neighborhood to reside in.

Household mobility. In my model in Section 4, the parameter σ^{-1} crucially governs the extensive margin of housing demand. The parameter σ^{-1} characterizes the dispersion of household idiosyncratic preferences for neighborhoods. Intuitively, it can be interpreted as a measure of household mobility. Larger values of the parameter σ^{-1} suggest that households are more sensitive to housing prices when choosing a neighborhood. To estimate household mobility, I use geographic variation in housing supply elasticity as a source of identification. Standard economic theory suggests that the extent to which housing demand shocks increase housing prices is dependent on housing supply elasticity. In the extreme, when supply is perfectly elastic, 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:

[39] Given a normalization of the price of non-housing consumption p_j, the parameters α_j are uniquely identified. For counterfactual simulations, I normalize the price of non-housing consumption to $p_j = 1$.

$$\frac{\partial \log\left(r_j\right)}{\partial A_j} \approx \frac{\sigma^{-1}}{\gamma_j + \eta + (1-\eta+\sigma^{-1})\, E\left[S\right]} E\left[\beta\right] \tag{7}$$

where γ_j is housing supply elasticity, η is the parameter governing the intensive margin elasticity of housing demand, σ^{-1} is the parameter governing the extensive margin elasticity of housing demand, $E\left[S\right]$ is the average housing expenditure share, and $E\left[\beta\right]$ 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:

$$\gamma_j \to \infty \implies \frac{\partial \log\left(r_j\right)}{\partial A_j} \to 0$$

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

To observe exogenous changes in local public goods, I follow the quasi-experimental 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.[40] That is, I use differences in standardized test scores as a proxy measure for exogenous housing demand shocks. I then compare houses across school district borders, controlling for tax rates and housing characteristics.[41] Crucially, I only compare houses across school district borders within the same municipality, ensuring similarity in non-education local public goods.[42] 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.[43] The key identification assumption I make is that discrete changes in unobserved quality at school district borders within the same municipality are uncorre-

[40]I use the average school grade and cohort-adjusted standardized test score pooled across all subjects for a given school district from 2009 to 2019.

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

[42]Figure 4 presents an example of a school district boundary within a municipality. In this example, houses located in Saratoga City can belong to one of two school districts: Cupertino Union School District or Saratoga Union School District.

[43]I use housing supply elasticities from Baum-Snow and Han (2024). Estimates of housing supply elasticities from Baum-Snow and Han (2024) are provided at the census-tract level. I aggregate housing supply elasticities to a municipality level following the recommended methodology in Baum-Snow and Han (2024).

lated with discrete changes in housing supply elasticity–notably, zoning.[44]

In particular, I estimate the regression equation:

$$\begin{aligned}\log(p_{it}) = {} & \beta^{-1.0} \cdot \mathbb{I}(-1km \leq Dist_{it} < -0.9km) \cdot \Delta Test_{b_i} \times Supply_{m_i} + \ \ldots \ + \\ & \beta^{1.0} \cdot \mathbb{I}(1km \leq Dist_{it} < 1.1km) \cdot \Delta Test_{b_i} \times Supply_{m_i} + \\ & \delta X_{it} + \lambda_{b_i t} + \varepsilon_{it}\end{aligned} \tag{8}$$

where p_{it} is the sale price per square feet for house i in year t, $Dist_{it}$ is distance to the school district border, $\Delta Test_{b_i}$ is the change in test scores across the school district border b_i, $Supply_{m_i}$ is an indicator whether municipality m_i 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. I standardize distance such that housing transactions with a positive distance are located in school districts with higher test scores, and cluster standard errors by school district border.

Figure 14 presents the regression coefficients for β when estimating equation (8). In contrast, Figure 15 presents the regression coefficients for β when estimating equation (8) without including interaction terms for housing supply elasticity:

$$\begin{aligned}\log(p_{it}) = {} & \beta^{-1.0} \cdot \mathbb{I}(-1km \leq Dist_{it} < -0.9km) \cdot \Delta Test_{b_i} + \ \ldots \ + \\ & \beta^{1.0} \cdot \mathbb{I}(1km \leq Dist_{it} < 1.1km) \cdot \Delta Test_{b_i} + \\ & \delta X_{it} + \lambda_{b_i t} + \varepsilon_{it}\end{aligned}$$

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 the household mobility parameter σ^{-1}. Motivated by equation (7), I estimate the following regression equation using housing transactions within 0.5 kilometers of a school district border:

$$\begin{aligned}\log(p_{it}) = {} & Dist_{it} \times \mathbb{I}(Dist_{it} \geq 0km) + Dist_{it} \cdot \Delta Test_{b_i} \times \mathbb{I}(Dist_{it} \geq 0km) + \\ & \frac{\sigma^{-1}}{\gamma_{m_i} + \eta + (1 - \eta + \sigma^{-1}) E[S]} E[\beta] \cdot \Delta Test_{b_i} \cdot \mathbb{I}(Dist_{it} \geq 0km) + \\ & \delta X_{it} + \lambda_{b_i t} + \varepsilon_{it}\end{aligned} \tag{9}$$

[44] I do not observe jumps in housing density, as measured by floor area ratios, across school district boundaries (Appendix Figure A.5). In contrast, I do observe jumps in property tax rates across school district boundaries (Appendix Figure A.6).

where p_{it} is the sale price per square feet for house i in year t, $Dist_{it}$ is distance to the school district border, $\Delta Test_{b_i}$ is the change in test scores across the school district border b_i, γ_j is the housing supply elasticity for municipality m_i, δX_{it} are covariates (e.g., house age, lot size, property tax rate), and λ_{b_it} are border-year fixed effects. To operationalize equation (9), I set $\eta = 0.27$ as estimated in Table 1 and calibrate $E[S] = 0.3$ to match the average housing expenditure share in my data. I standardize distance such that housing transactions with a positive distance are located in school districts with higher test scores, and cluster standard errors by school district border. Table 2 presents the results: I estimate $\sigma^{-1} = 9.2$, which can be approximately translated to households having a share outmigration elasticity of 9.2 with respect to income.[45]

Migration patterns. 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. Intuitively, the distribution of ε_{ij} governs household migration patterns; i.e., where a household chooses to move given outmigration. I use household migration data from Infutor Data Solutions to estimate the parameters of the generalized extreme value distribution. Specifically, suppose household i has the following idiosyncratic preferences for school district j in commuting zone C_j in year t:

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

Figure 16 graphically presents the nesting structure for idiosyncratic preferences. The parameter λ_1 governs the likelihood that a household chooses to move school districts, 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 C_j in year t is given by:

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

[45] 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 for metropolitan areas.

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 migration parameters λ_1 and λ_2. Intuitively, net migration identifies changes in non-idiosyncratic utility v_{jt} for a given school district: school districts that become more desirable over time must also experience population growth.[46] Accounting for changes in non-idiosyncratic utility via net migration, gross migration then identifies the parameters λ_1 and λ_2. If households typically do not move away from their original school district, this suggests $\lambda_1 \approx 0$. Conditional on moving, if households typically move to new school districts in the same commuting zone, this suggests $\lambda_2 \approx 0$. I estimate $\lambda_1 = 0.16$ and $\lambda_2 = 0.39$ via method of simulated moments.[47] In particular, I use the share of households that stay in their original school district as a moment to identify the parameter λ_1. I use the share of households that move school districts but stay in their original commuting zone as a moment to identify the parameter λ_2. Figure 17 graphically presents the moment equations used to estimate the parameters of the generalized extreme value distribution.

6 Counterfactuals

To examine the welfare effects of local property taxation, 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. Head taxes, by virtue of their non-distortionary nature, offer a theoretically efficient benchmark.

To simulate household welfare, I use the housing demand parameters that I causally estimate in Section 5.1 (i.e., the parameters $\delta_{\theta j}$, η, α_θ, and α_j) and Section 5.2 (i.e., the parameters σ^{-1} and λ_2). I calibrate housing supply elasticities (i.e., the parameter γ_j) using causal estimates from Baum-Snow and Han (2024).[48] Additionally, I allow neighborhood-specific productivity to differ by commuting zones, where I calibrate productivity differences (i.e., i.e., the parameter β_j) using causal estimates from Card, Rothstein, and Yi (2025).[49] The only remaining parameters I

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

[47] I approximate the CDF of a three-level nested logit via Fourier inversion on the characteristic function of an extreme value type I distribution.

[48] Baum-Snow and Han (2024) provides estimates of housing supply elasticities at the census-tract level. I follow the recommended methodology in Baum-Snow and Han (2024) to aggregate housing supply elasticities at a school district level. Furthermore, I assume that housing supply elasticities are identical for low-quality versus high-quality housing. This is approximately equivalent to assuming that low-quality and high-quality housing supply elasticities in a given neighborhood are each half of total housing supply elasticity for the neighborhood.

[49] Card, Rothstein, and Yi (2025) provides causal estimates for the effects of location on earnings. I interpret the

do not observe are neighborhood-specific amenities $\beta_\theta A_j$, which I uniquely identify by inverting income-specific population shares $S_{\theta j}$ following Berry (1994). To ensure that my household income distributions are representative of the national distribution, I use income-specific household population shares in 2019 from the 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.[50]

Since my housing demand parameters are estimated from an external sample of households, the observed rents and tax rates in my data may not characterize an equilibrium.[51] 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 18 presents the model-implied nominal intrajurisdictional redistribution in 2019, benchmarked to observed nominal intrajurisdictional redistribution that occurred in 2019. I find that model-implied nominal intrajurisdictional redistribution in 2019 matches observed redistribution.

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 19), leading to a 2% increase in housing supply (Figure 20). 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 21). 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 22).

I then simulate counterfactual rents and tax rate for a universal progressive property tax sys-

effects of location on earnings as measures of total factor productivity.

[50]The Supplementary Poverty Measure combines pre-tax household income from the American Community Survey with the TAXSIM calculator from the National Bureau of Economic Research to measure post-tax household resources.

[51]I impute owners' equivalent rent following the procedure in Section 5.1 using property values from 2019 property tax assessments. I use property tax assessments instead of property transactions since property tax assessments are comprehensive, meaning that definitions of low- and high-quality housing are absolute. In the majority of states, property values are legally mandated to reflect fair market value, and assessor offices use prior sales transactions to predict the market values (Appendix Figure A.1). I impute rental tax rates using property tax rates from 2019 property tax assessments following the procedure in Section 5.1.

tem with increasing marginal tax rates, where housing consumption is taxed at one rate before a threshold, and taxed at a higher rate after the threshold. In particular, I establish thresholds for each school district by using the 75th percentile of housing values within their respective counties in 2019. I simulate a series of increasingly 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 19), leading to a 1% decrease in housing supply (Figure 20). 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 equivalent 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 24). 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 24). 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 24).

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 0.3% in Hawaii to a maximum of 2.7% 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 that the elasticity of housing expenditure with respect to price is 0.51, rejecting a 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, proving a potential explanation for 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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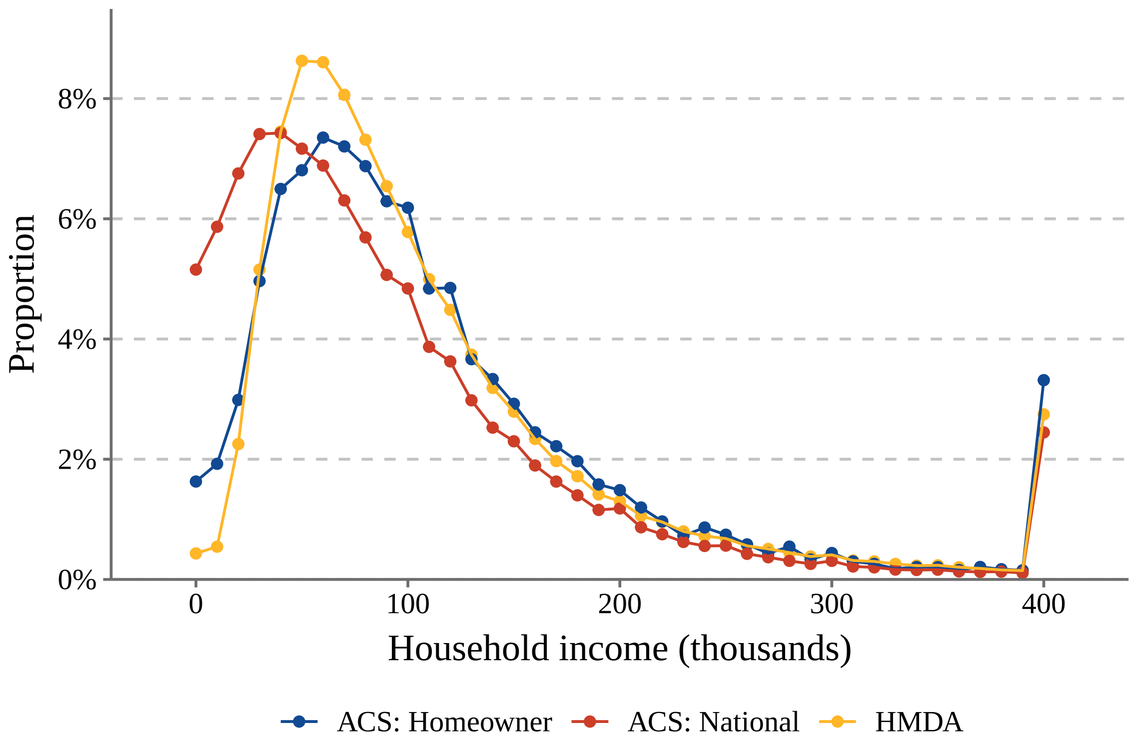
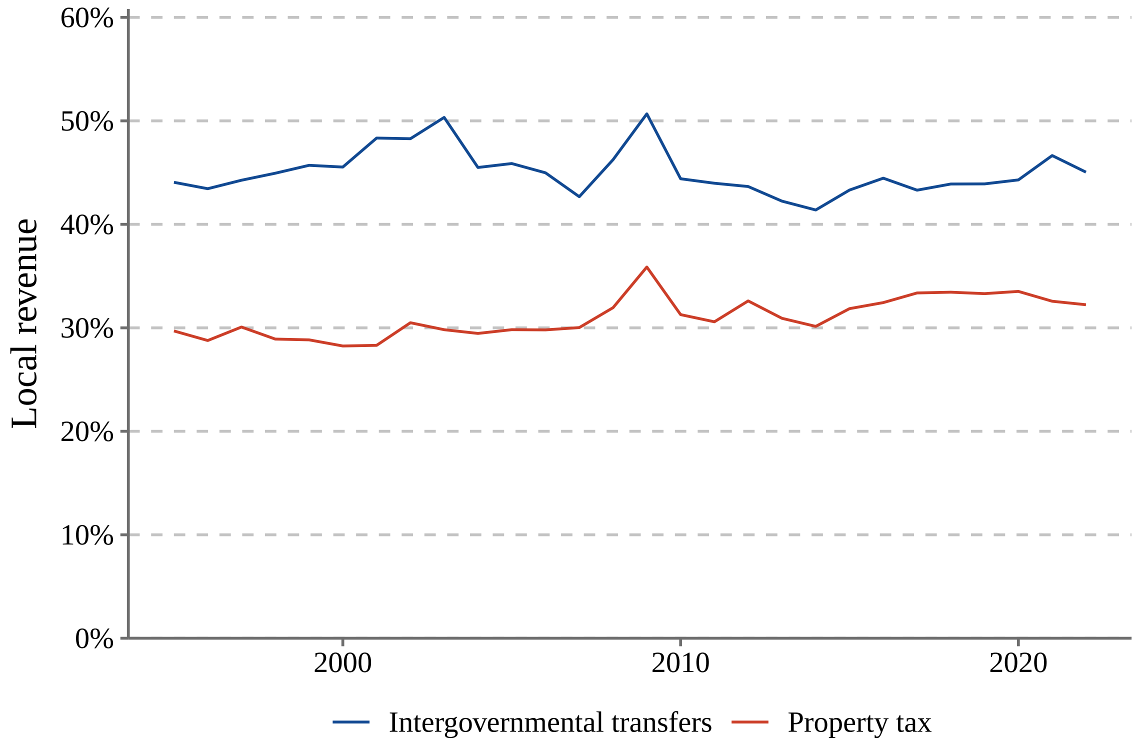
Figure 1: **Household income in 2019: HMDA vs. ACS**



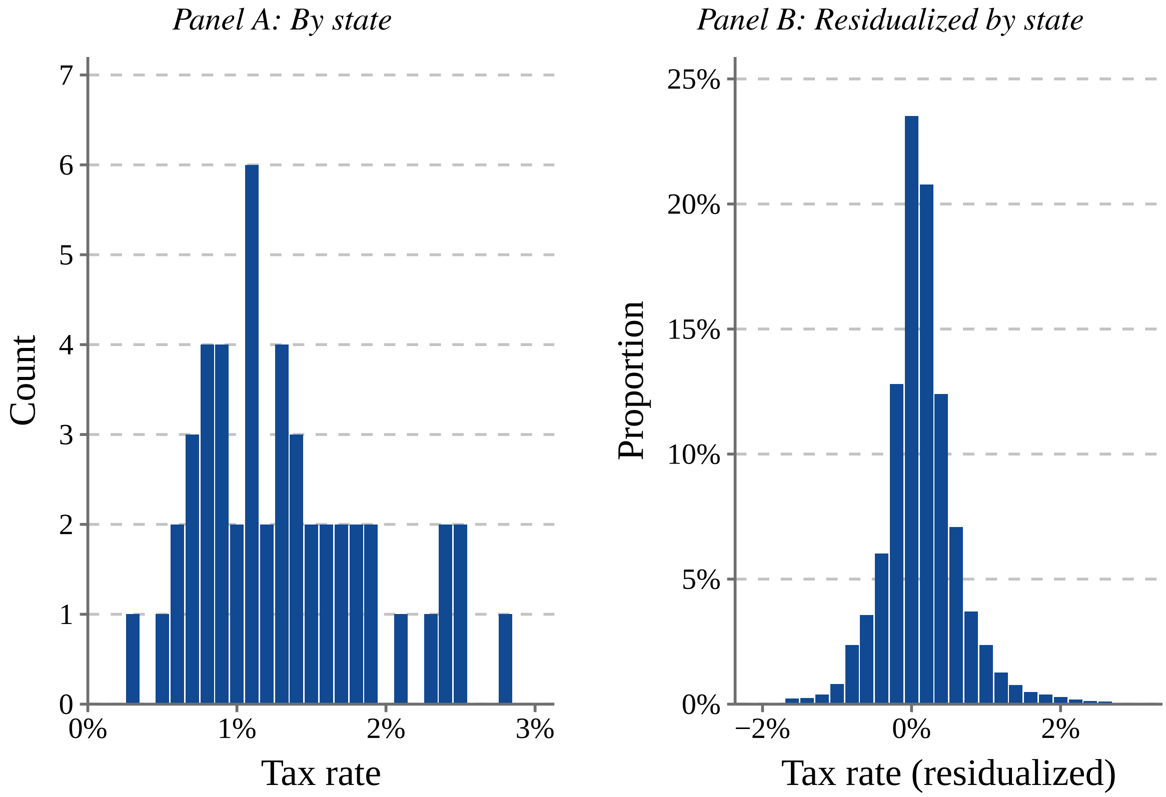
Note: This figure presents distributions of household income in 2019 across three samples: (1) the analysis sample which uses income information from the Home Mortgage Disclosure Act (HMDA), (2) the national population in the American Community Survey (ACS), and (3) homeowners who recently purchased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

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



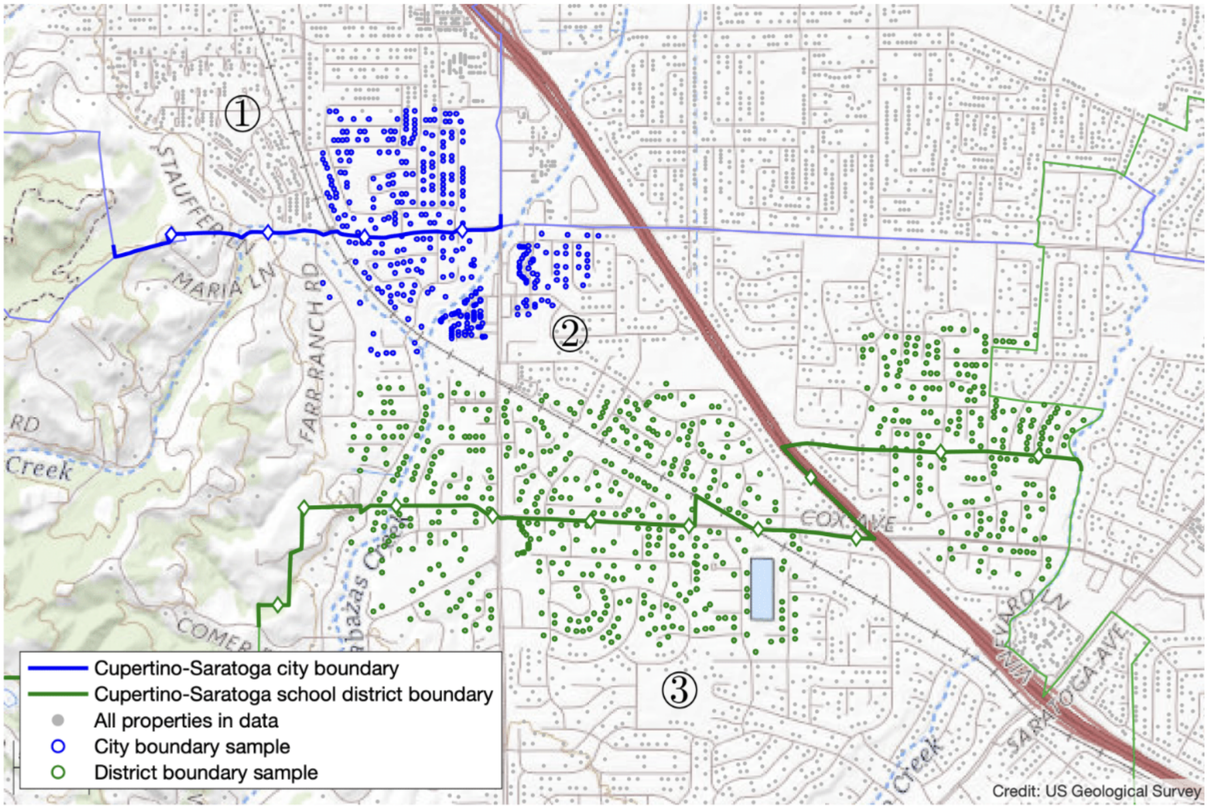
Note: This figure presents the share of local government revenue from different sources from 1970 to 2021 according to the Census of Governments. When measuring revenue, charges from public hospitals are excluded, as such charges are direct payments for medical services.

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



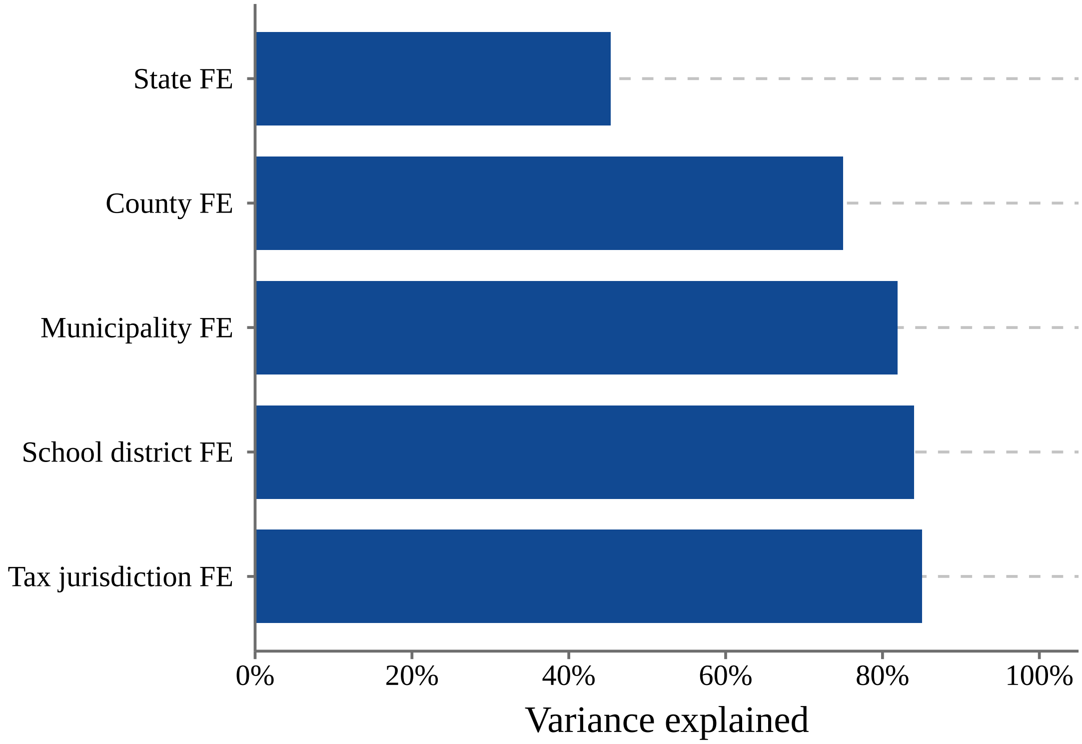
Note: Panel A of this figure presents the distribution of median residential property tax rates in 2021 aggregated at the state level. Panel B of this figure presents the distribution of residential property tax rates in 2021 after residualizing by state-specific median values.

Figure 4: **Example of misaligned city and school district boundaries**



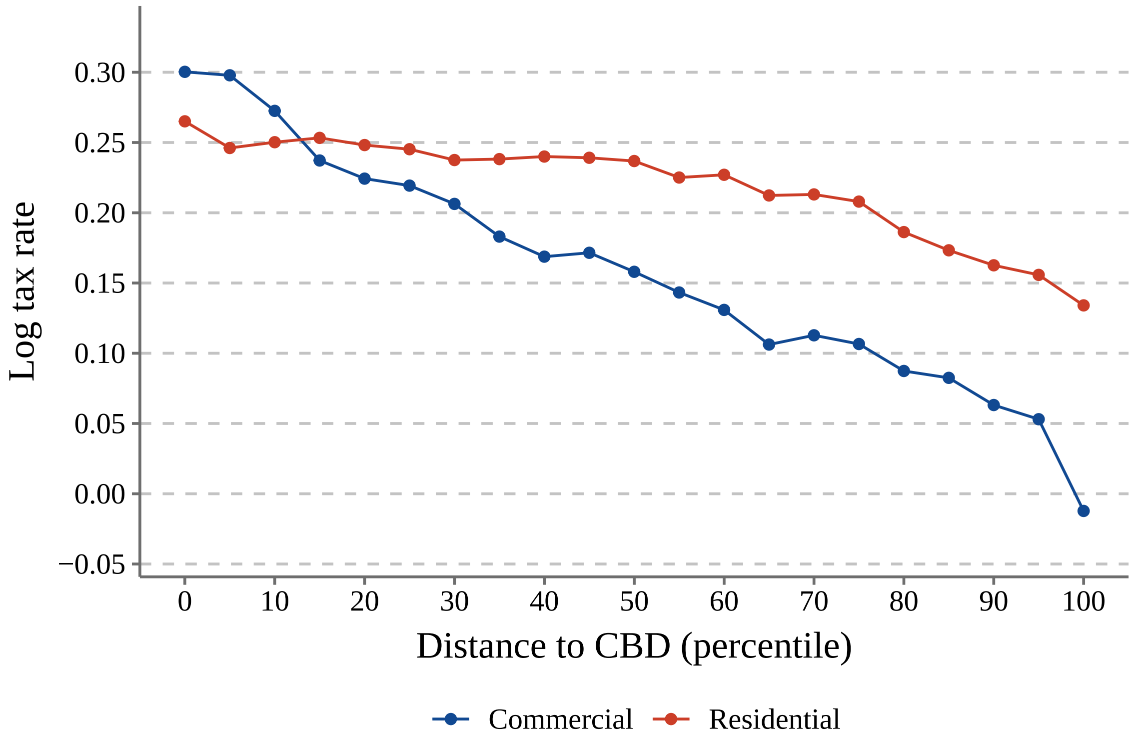
Note: This figure presents an example from Schonholzer (2024) of when municipality boundaries and school district boundaries are misaligned. Properties belong to one of three tax jurisdictions: (1) Santa Clara County/Cupertino City–Cupertino Union School District; (2) Santa Clara County–Saratoga City–Cupertino Union School District; and (3) Santa Clara County–Saratoga City–Saratoga Union School District.

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



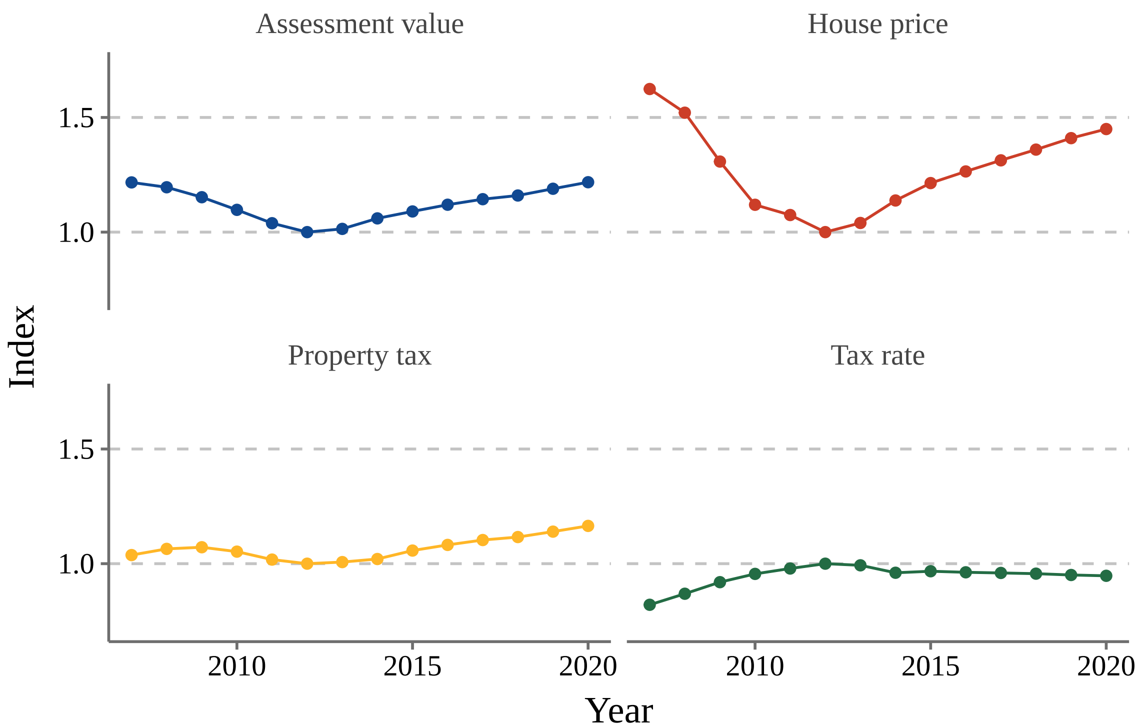
Note: This figure presents the proportion of variation in residential property tax rates explained by different levels of government in 2019. Tax jurisdiction refers to the specific combination of county, municipality, and special districts to which a parcel belongs.

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



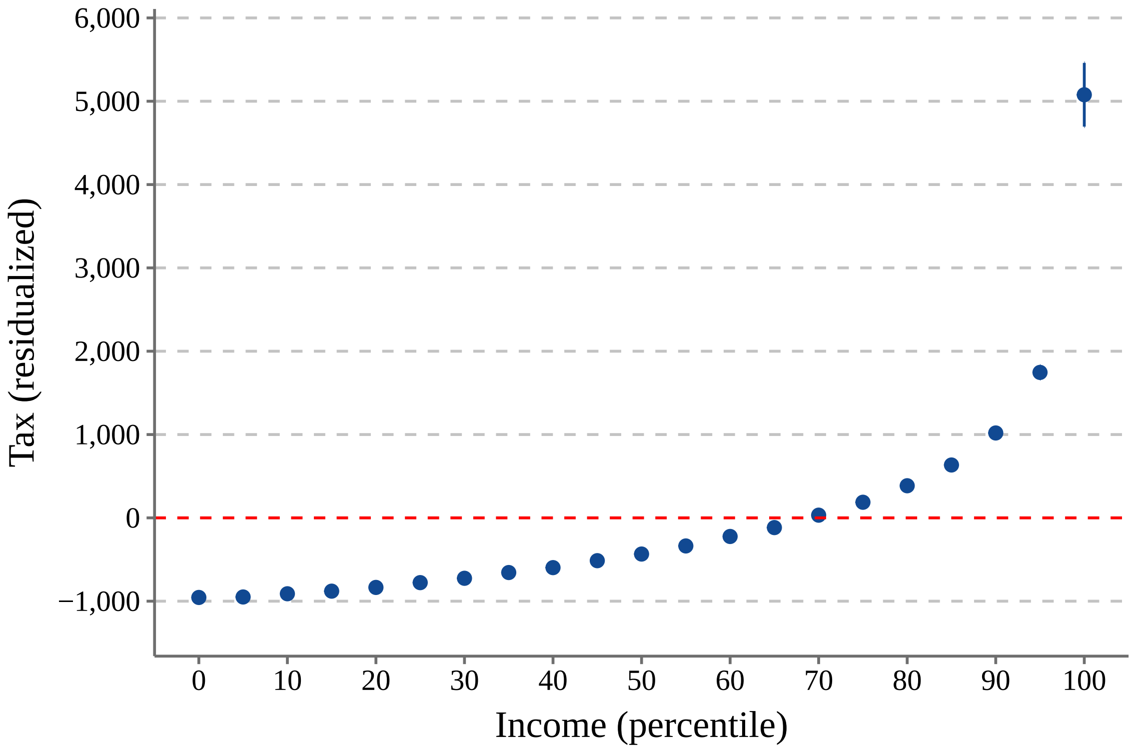
Note: This figure presents a binscatter analysis of property tax rates by percentile of distance from the nearest central business district (CBD) in 2021. Percentile of distance from the nearest CBD is calculated relative to each metropolitan area, ensuring balanced representation in metropolitan areas across percentiles.

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



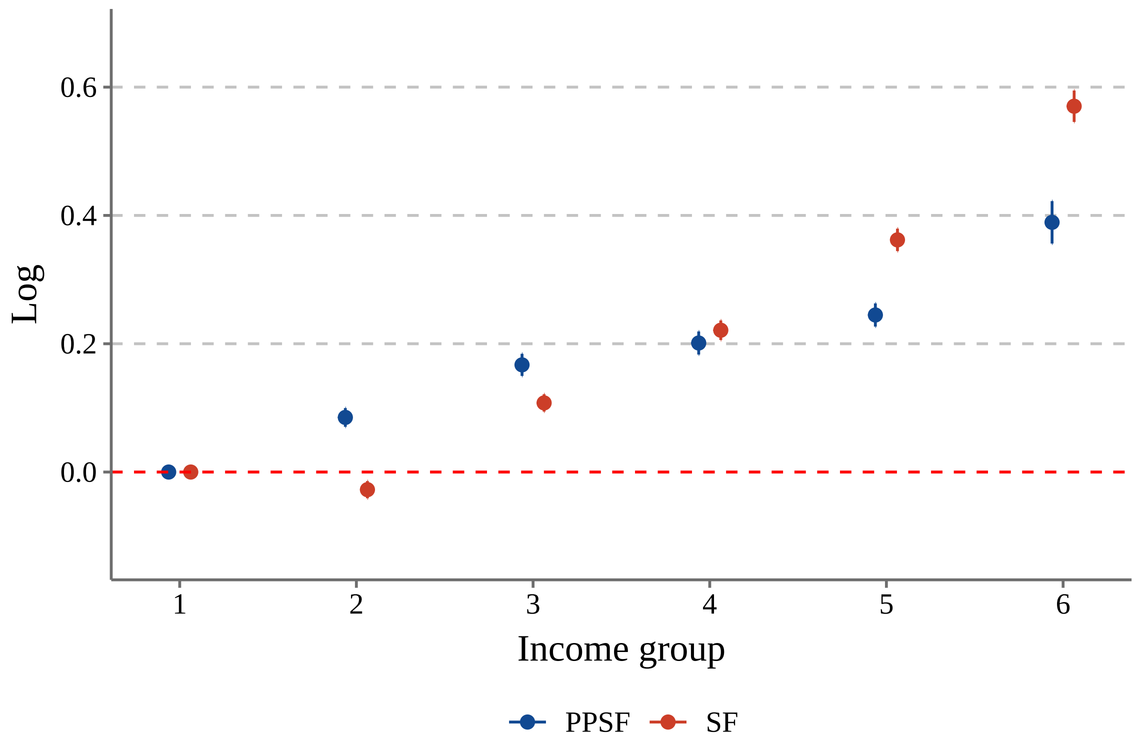
Note: This figure presents house price, property value, tax rate, and tax amount indices from 2007 to 2021. The house price index is constructed by following the repeat sales methodology from Case and Shiller (1987). To construct the property value, tax rate, and tax amount indices, I use a modified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

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



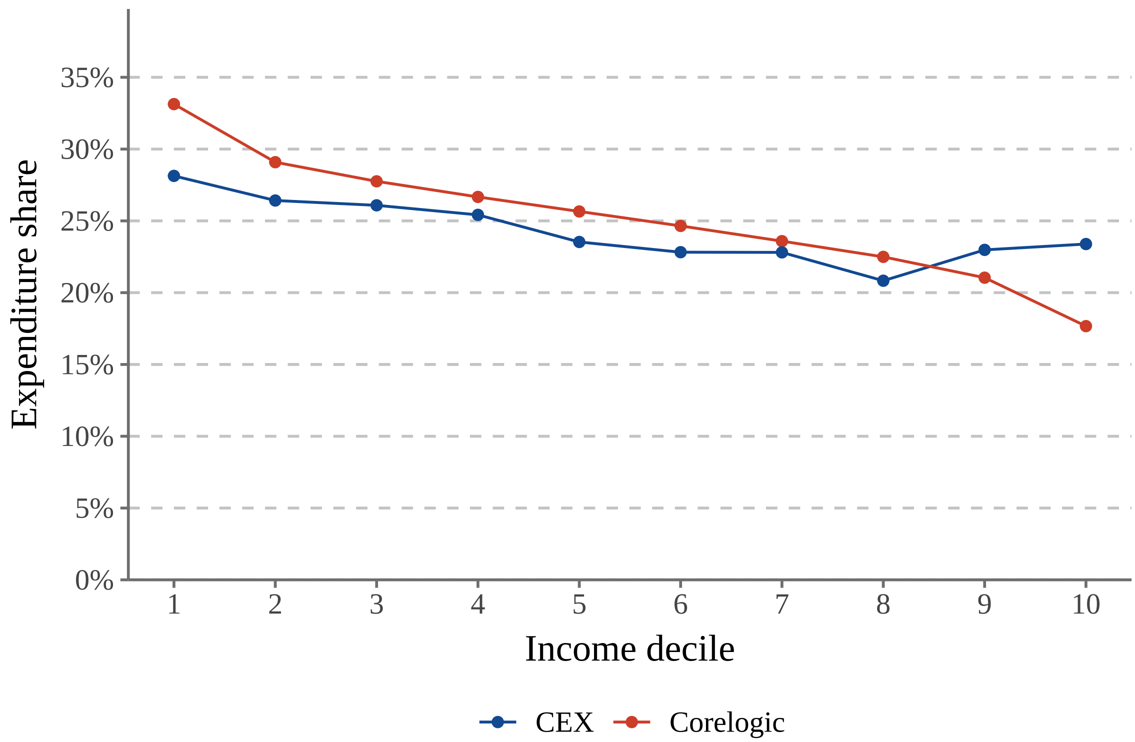
Note: This figure presents the estimated coefficients on household income percentile fixed effects for equation (1), where the outcome is property tax payment in 2019. Outcomes are ex-ante residualized by the average in the school district. Household income percentiles are defined using the national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



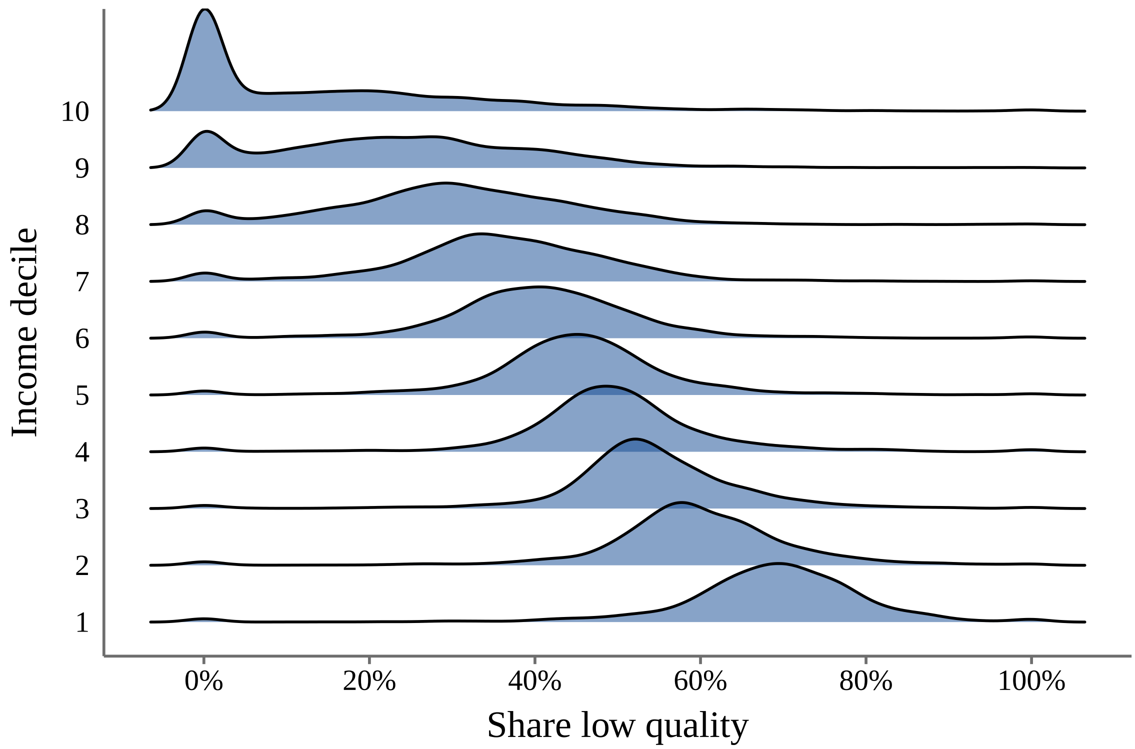
Note: This figure presents the estimated coefficients on household income group fixed effects for equation (2), where the outcomes are log house square footage and log price per square feet in 2019. Household income groups are defined as follows: (1) less than $25,000; (2) $25,000 to $49,999; (3) $50,000 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**



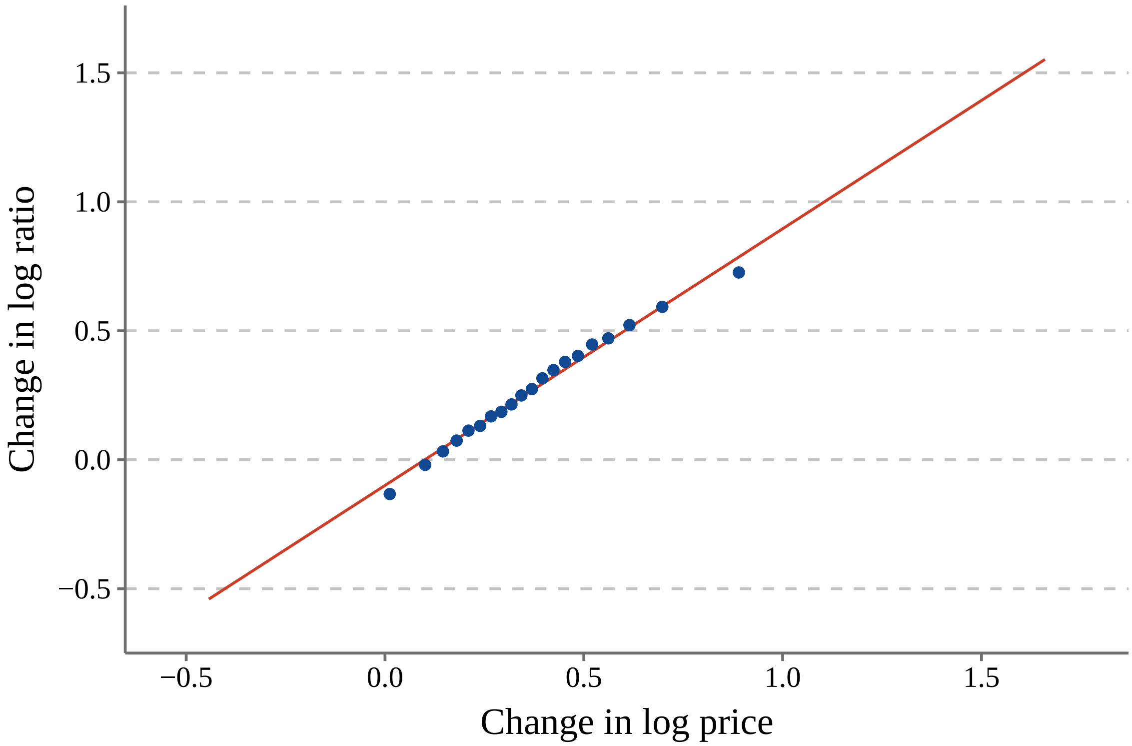
Note: This figure presents expenditure shares for housing by income group in 2019 across two samples: (1) the analysis sample; and (2) the 2019 Consumer Expenditure Survey (CEX). In the CEX, I exclude the following expenditures from housing: household operations, housekeeping supplies, and houshold furnishing and equipments.

Figure 11: **Distribution of taste parameter by income group, 2019**



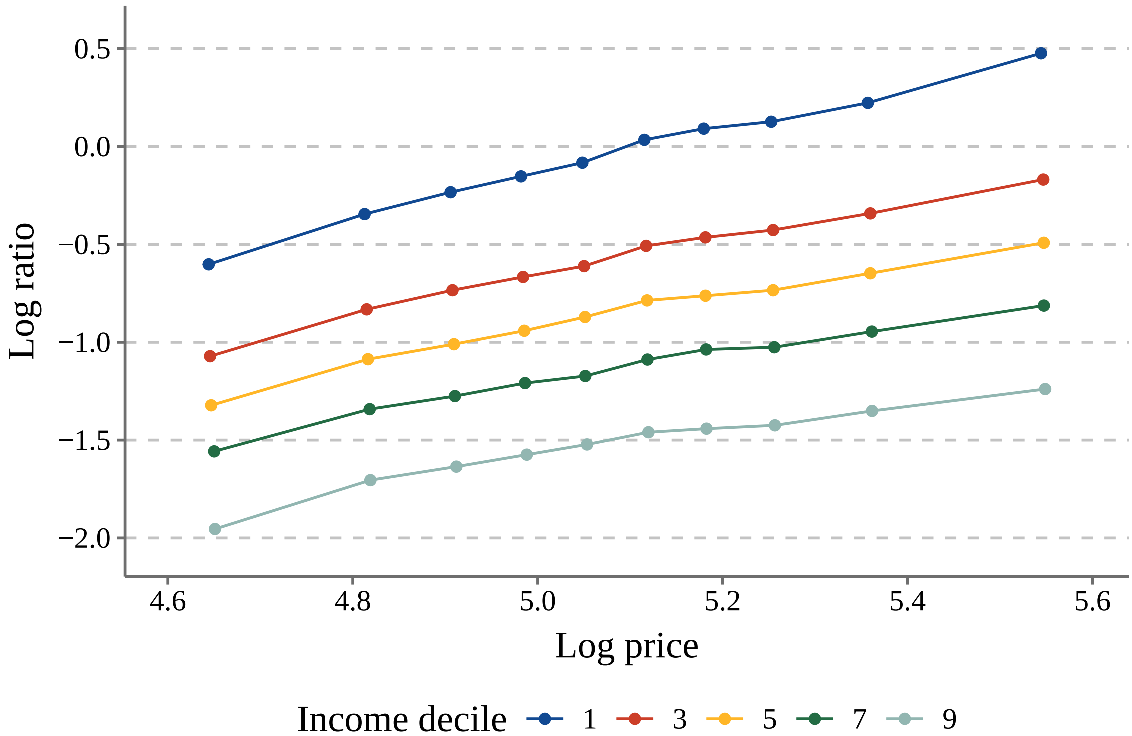
Note: This figure presents the distribution of the Cobb-Douglas parameter for the neighborhood-specific share of low-quality housing consumed by different income groups in 2019. A neighborhood is defined as a ZIP code.

Figure 12: **Binscatter of changes in housing expenditure share by changes in housing prices, 2010–2019**



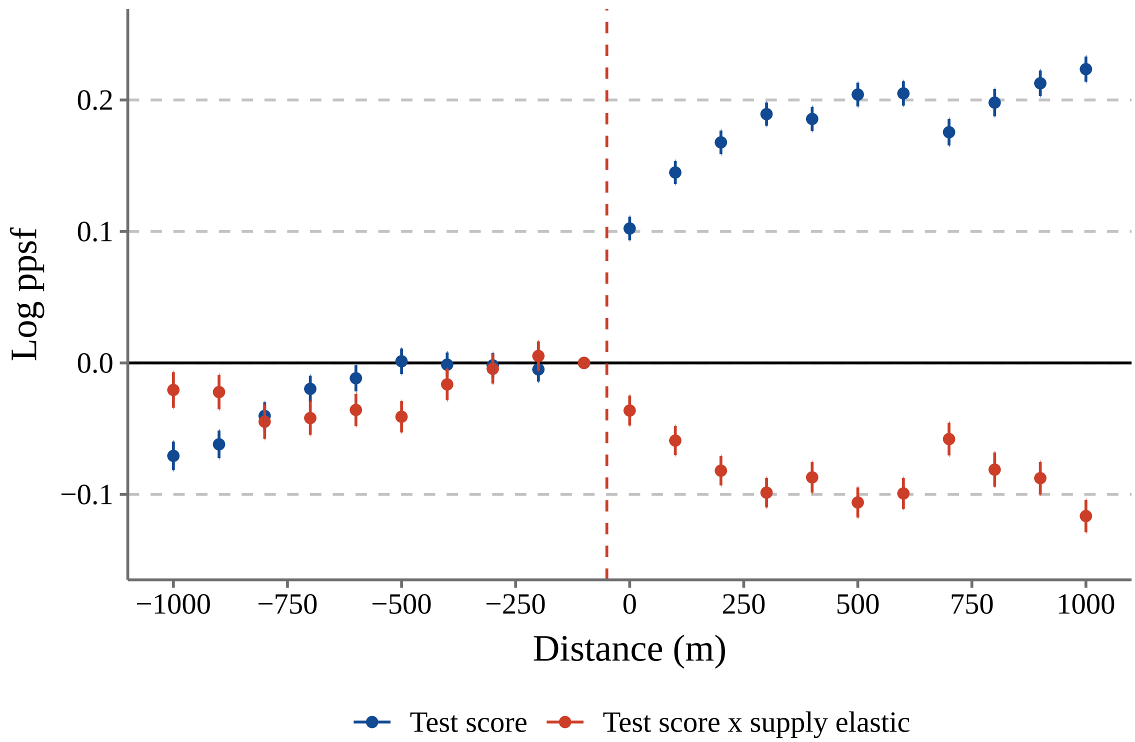
Note: This figure presents a binscatter analysis of changes in log housing expenditure share by changes in log housing prices from 2010 to 2019. Observations are at the ZIP code-income decile level.

Figure 13: **Binscatter of housing expenditure share by housing price, 2019**



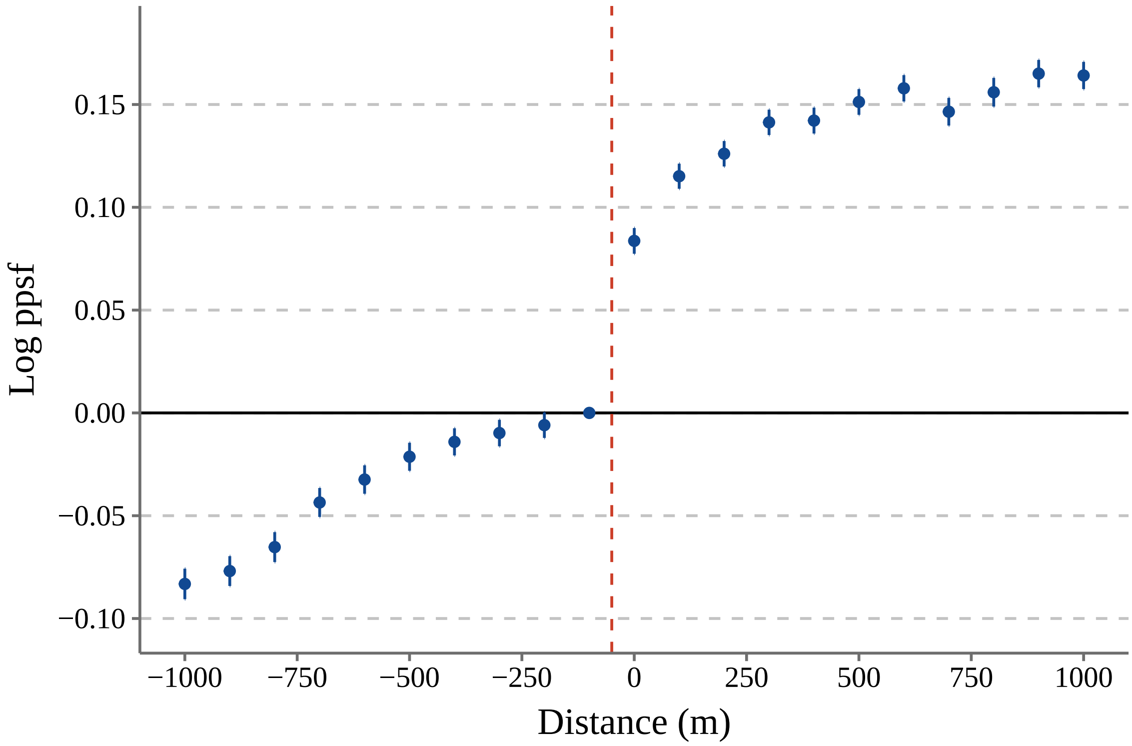
Note: This figure presents a cross-sectional binscatter of log housing expenditure share and log housing prices by income deciles in 2019. Observations are at the ZIP code-level.

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



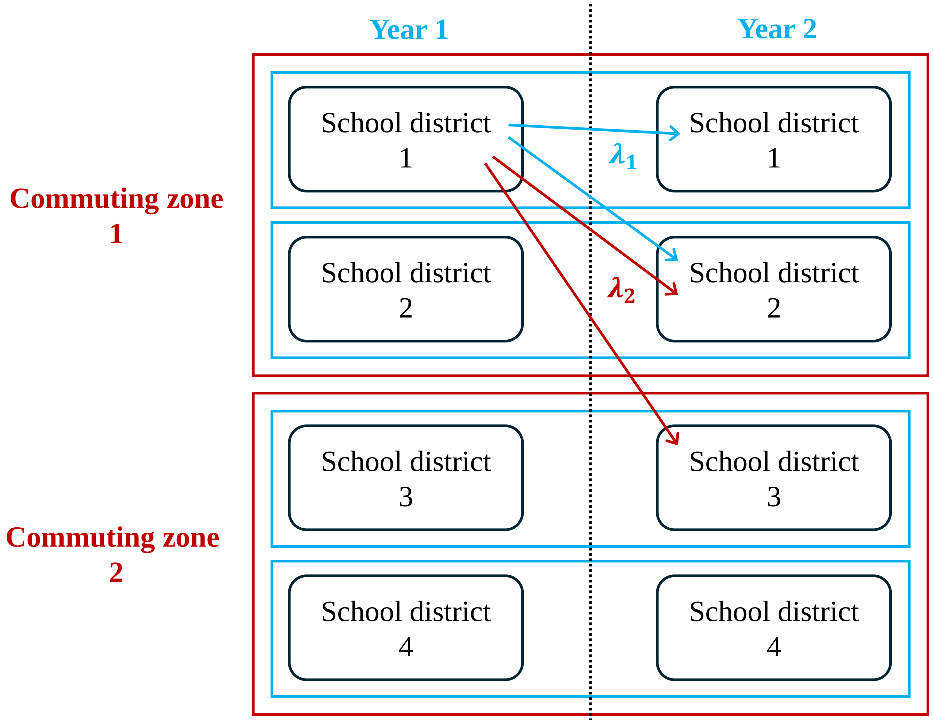
Note: This figure presents the coefficients from equation (8). Housing sales with a positive distance are located in school districts with higher test scores. Only school district boundaries located within the same municipality are included. Standard errors are clustered by school district boundary.

Figure 15: **Border discontinuity with school district boundaries, 2019**



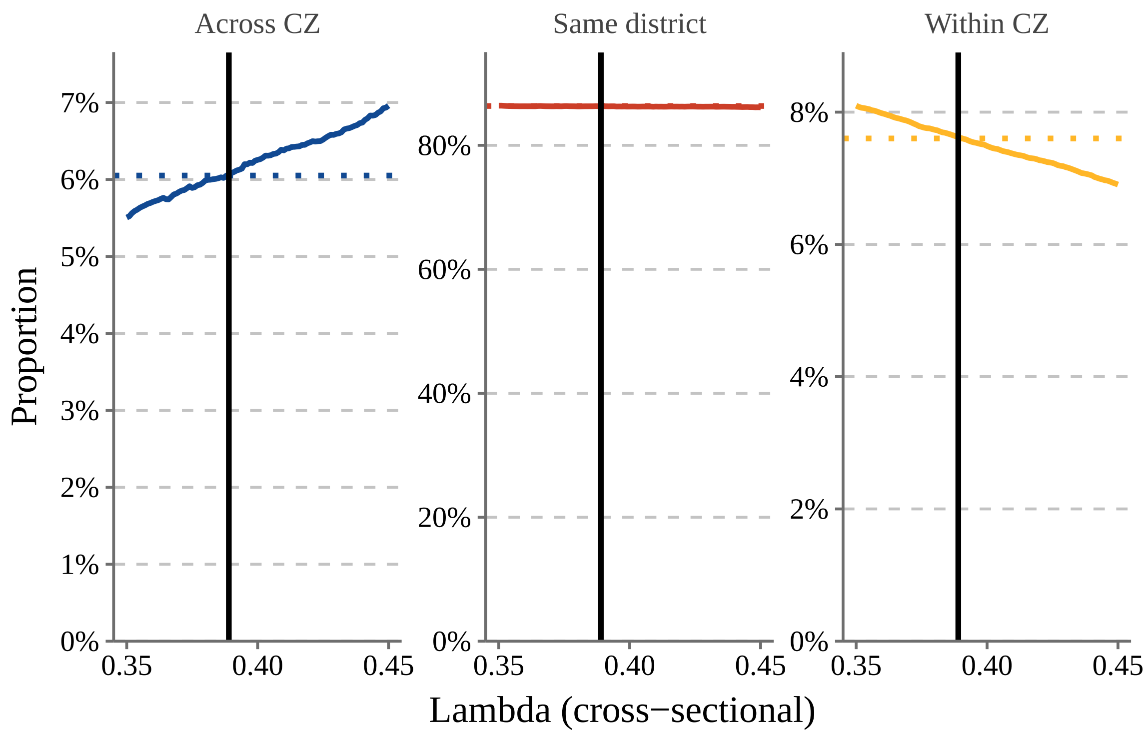
Note: This figure presents the coefficients from equation (8), without including interaction terms for housing supply elasticity. Housing sales with a positive distance are located in school districts with higher test scores. Only school district boundaries within the same municipality are included. Standard errors are clustered by school district boundary.

Figure 16: **Nesting structure for generalized extreme value distribution**



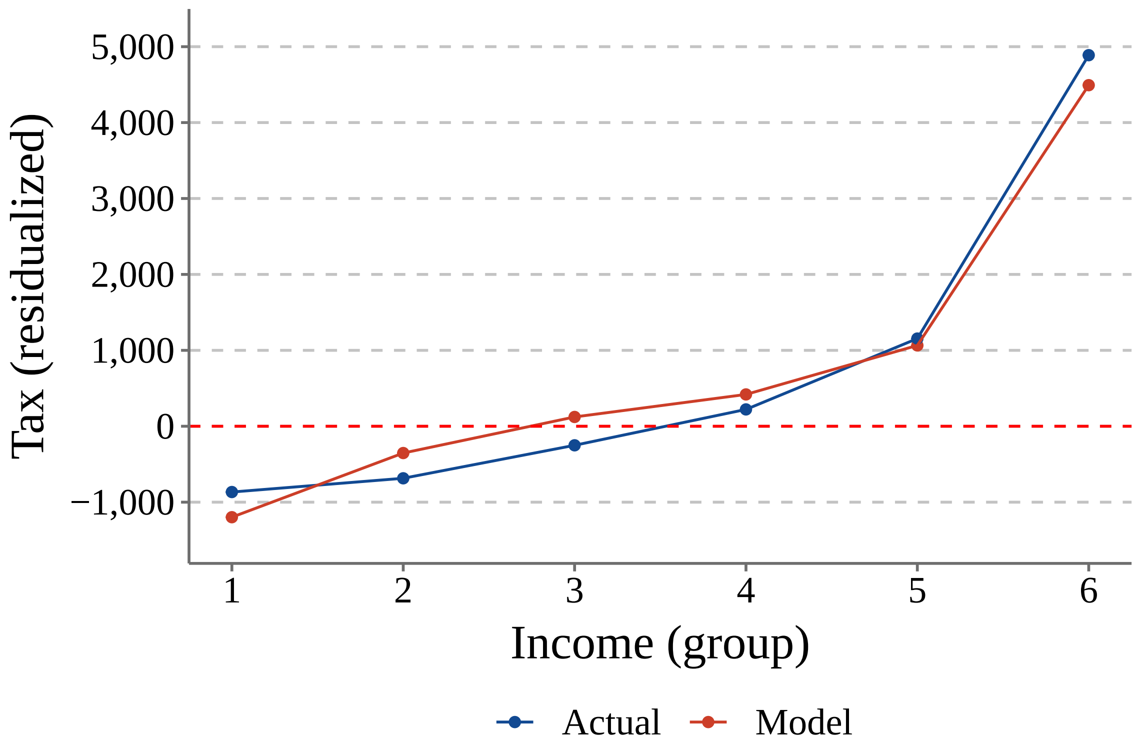
Note: This figure presents the nesting structure for the generalized extreme value distribution that characterizes household idiosyncratic preferences for school districts.

Figure 17: **Simulated versus actual migration, 2019**



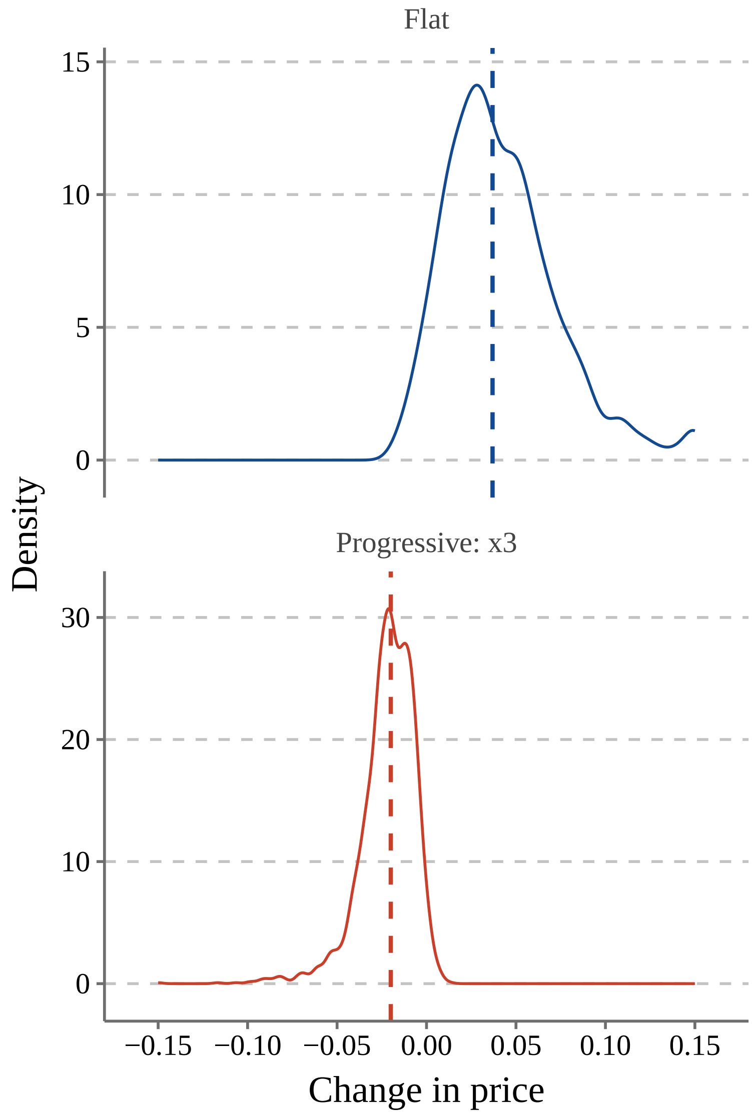
Note: This figure presents the moment equations used to identify the parameters of the generalized extreme value distribution. I fix $\lambda_1 = 0.16$ and present how gross migration shares change with the parameter λ_2. The dotted lines present the empirical moments for gross migration in the data.

Figure 18: **Model-implied nominal intrajurisdictional redistribution, 2019**



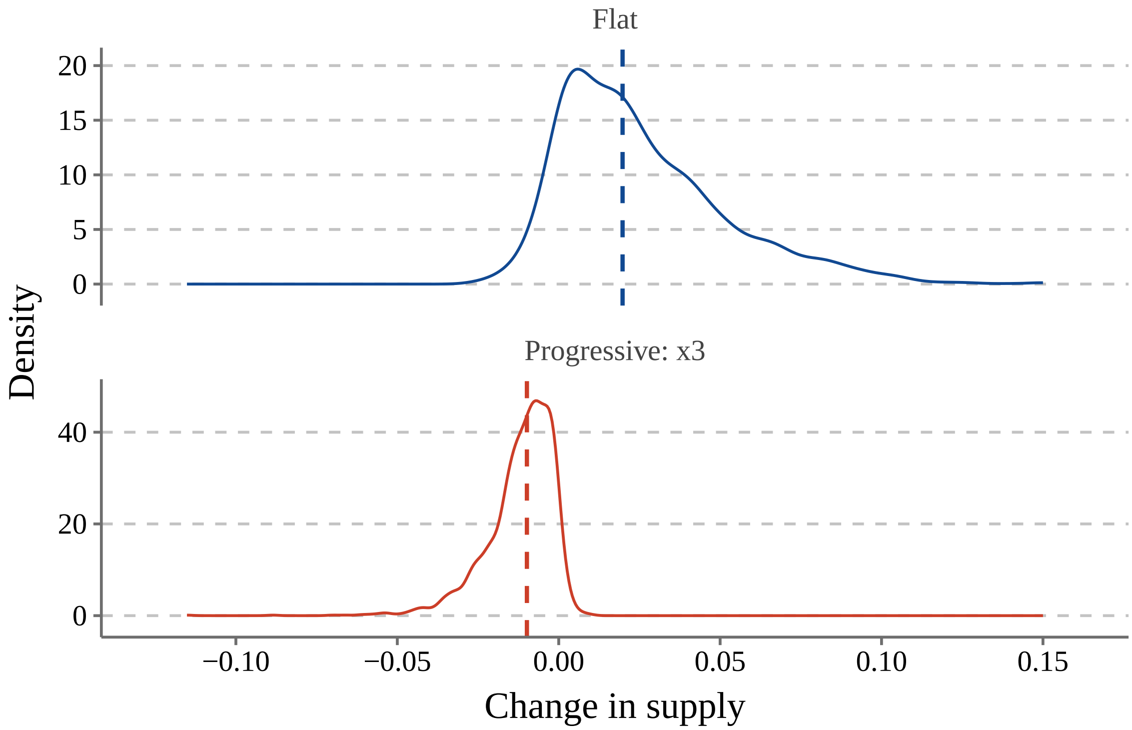
Note: This figure presents model-implied nominal intrajurisdictional redistribution by income group in 2019 using income-specific population shares from the Individual Income Tax Statistics. Model-implied nominal intrajurisdictional redistribution is benchmarked to nominal intrajurisdictional redistribution 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.

Figure 19: **Change in prices by school district, 2019**



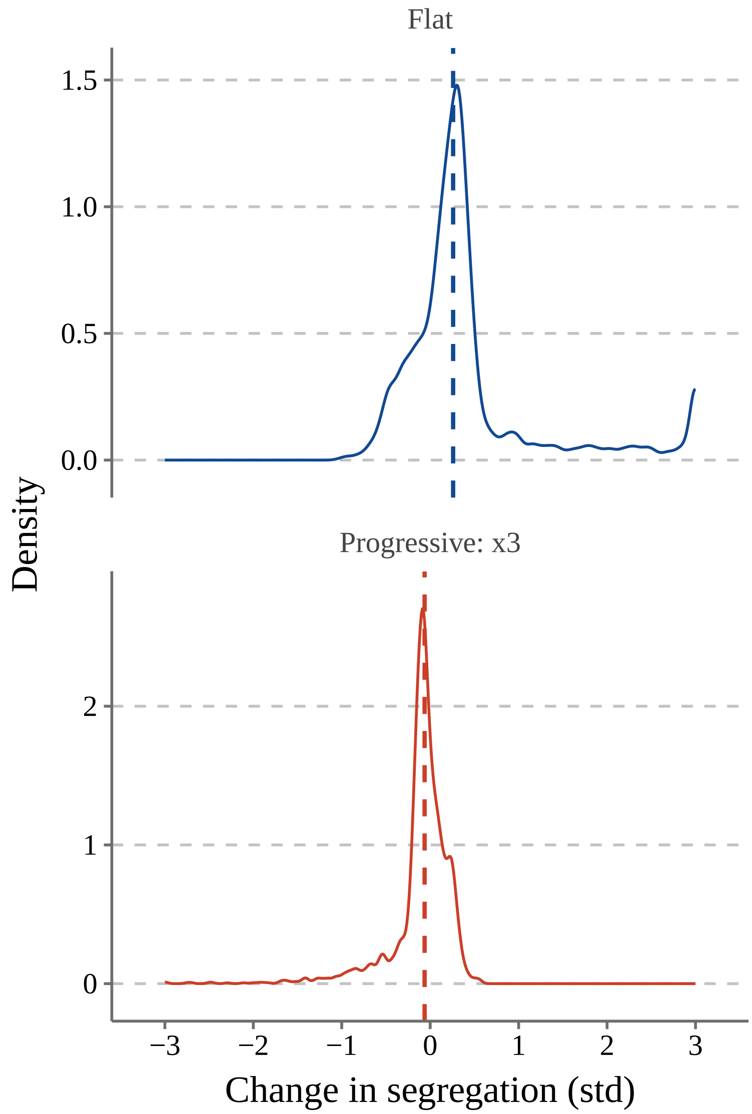
Note: This figure presents the distribution of changes in neighborhood-level average house prices switching from ad valorem property taxes to: (1) head taxes and (2) universal progressive property taxes where the marginal tax rate triples at the threshold.

Figure 20: **Change in square footage by school district, 2019**



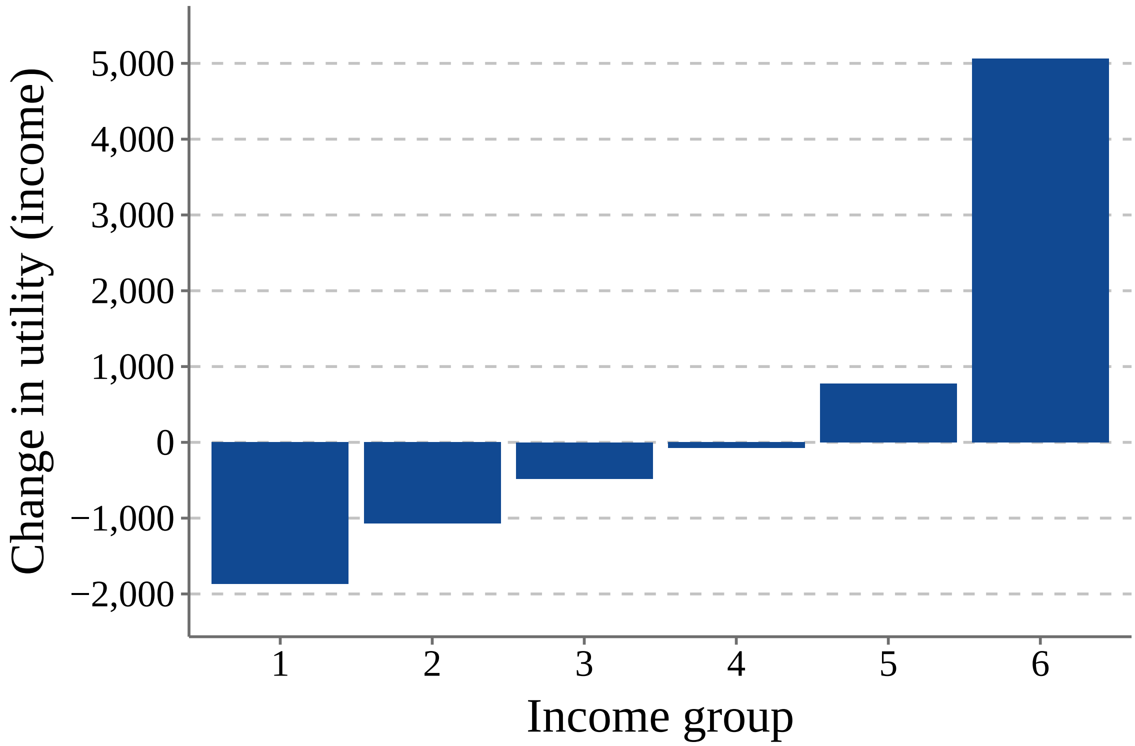
Note: This figure presents the distribution of changes in neighborhood-level total square footage switching from ad valorem property taxes to: (1) head taxes and (2) universal progressive property taxes where the marginal tax rate triples at the threshold.

Figure 21: **Change in segregation by school district, 2019**



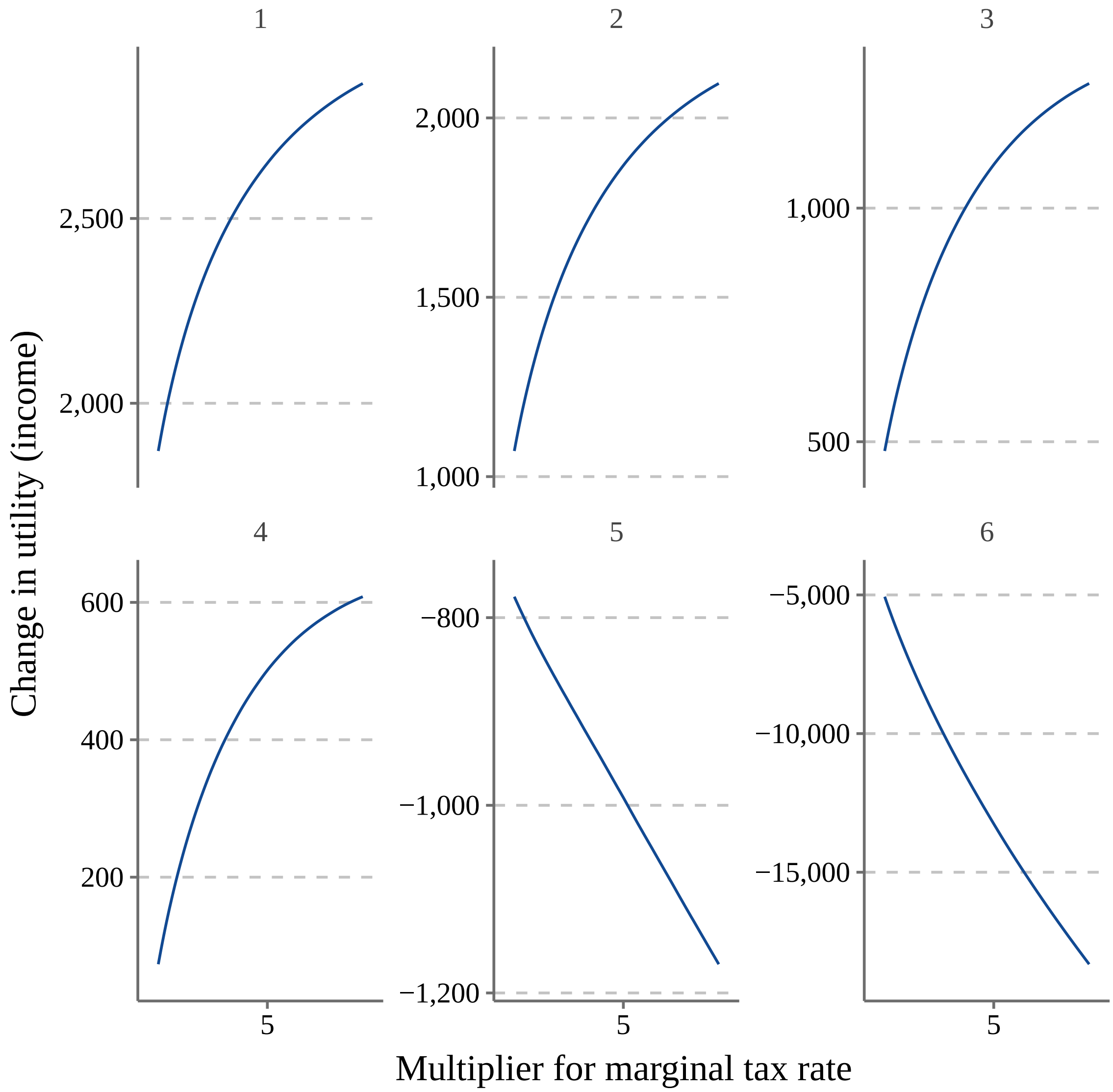
Note: This figure presents the distribution of changes in neighborhood-level segregation switching from ad valorem property taxes to: (1) head taxes and (2) universal progressive property taxes where the marginal tax rate triples at the threshold. Segregation is measured according to a dissimilarity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

Figure 22: **Welfare effect by income group: head tax, 2019**



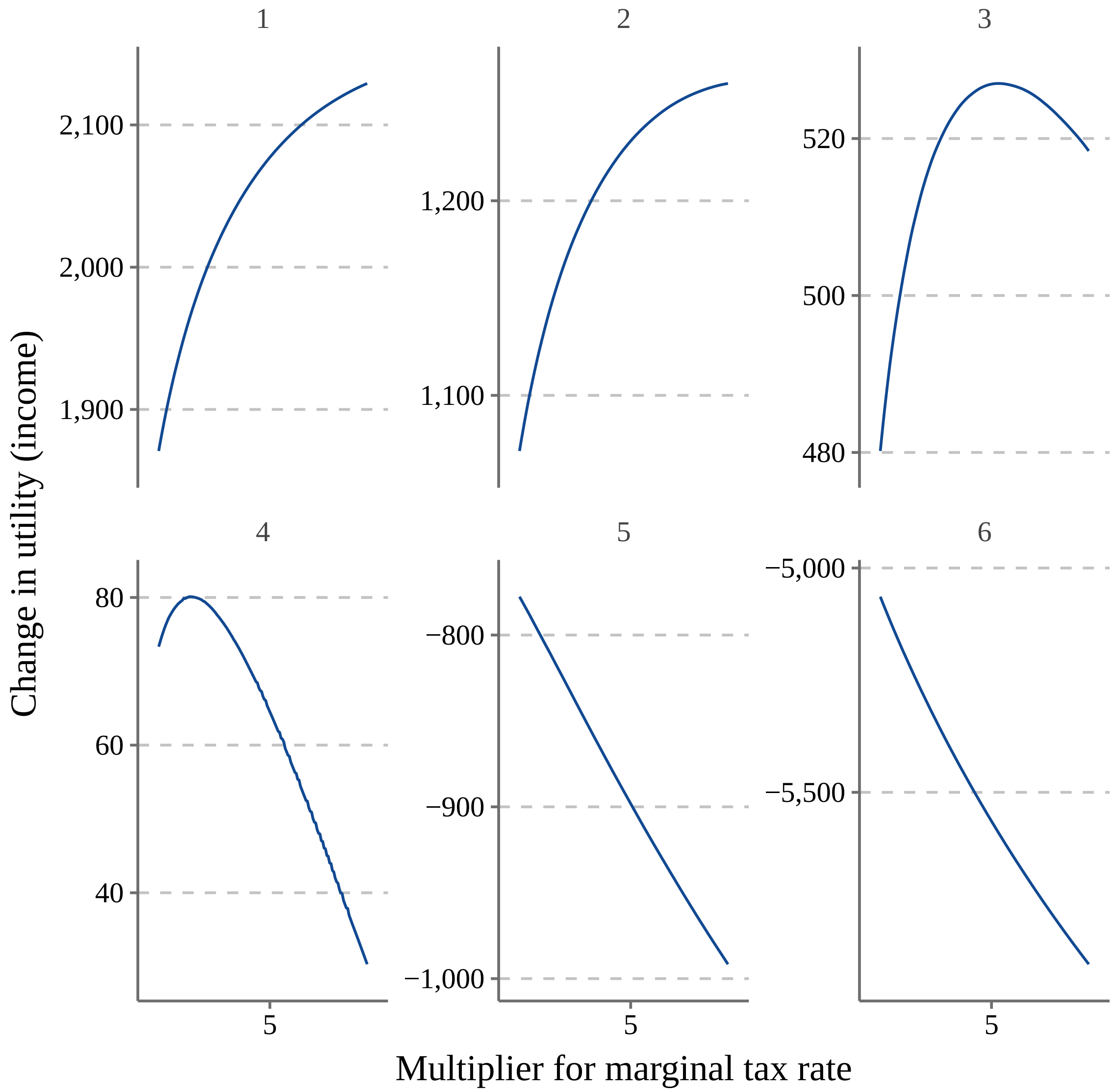
Note: This figure presents the welfare effects of switching from head taxes to ad valorem property taxes, where dollar amounts measure the compensating variation of the switch. Household income groups are defined as follows: (1) less than $25,000; (2) $25,000 to $49,999; (3) $50,000 to $74,999; (4) $75,000 to $99,999; (4) $100,000 to $199,999; and (6) $200,000 or more.

Figure 23: **Welfare effect by income group: universal progressive tax, 2019**



Note: This figure presents the welfare effects of switching from universal progressive property taxes to head taxes, where dollar amounts measure the compensating variation of the switch. 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 24: **Welfare effect by income group, partial progressive tax**



Note: This figure presents the welfare effects of switching from universal progressive property taxes to head taxes, where dollar amounts measure the compensating variation of the switch. 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

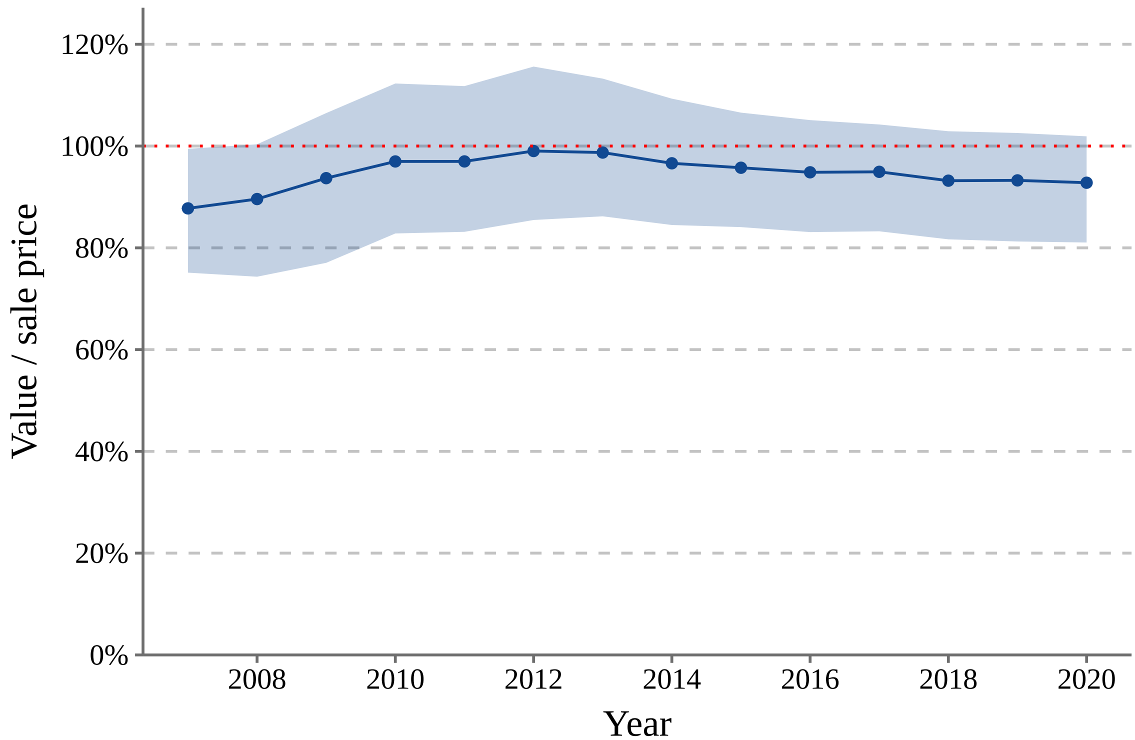
Table 2: **Outmigration elasticity, regression estimates**

	Coef.	Std. err.
$E[\beta]$	0.035	0.003
σ^{-1}	9.191	2.891

Apppendix

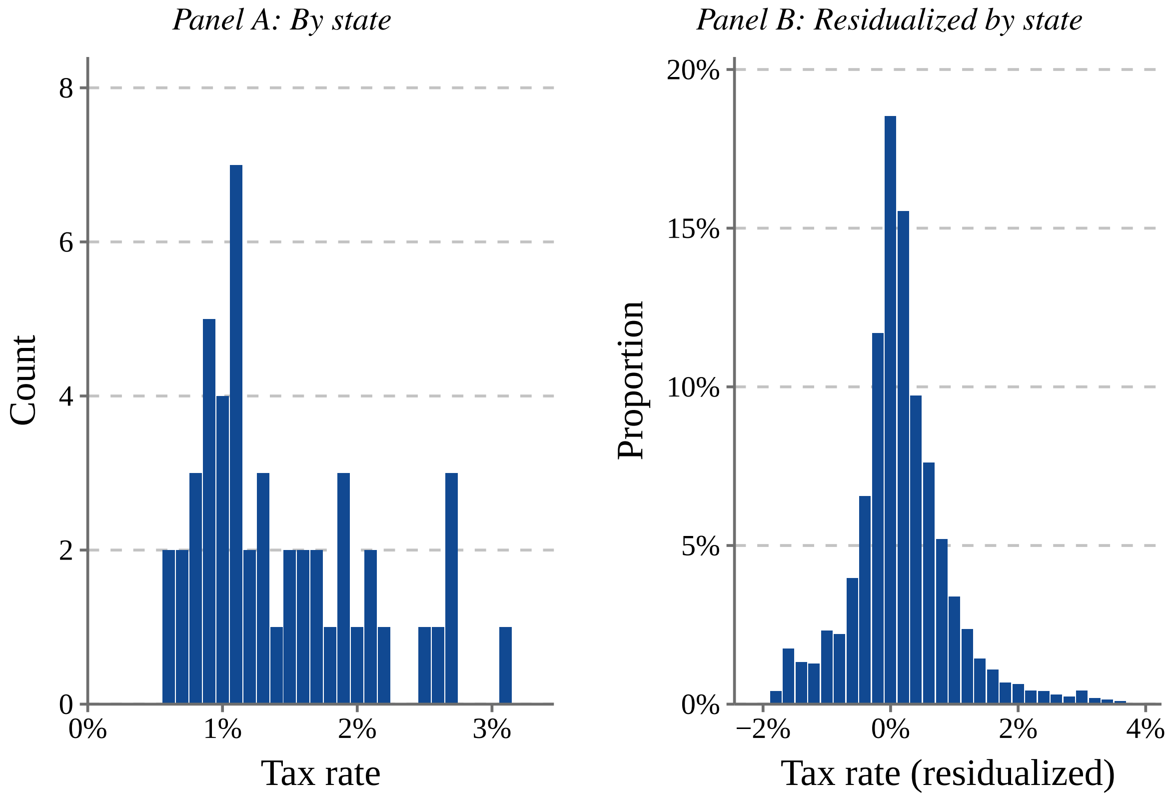
A Additional figures and tables

Figure A.1: **Property value to sale price ratio, 2007–2020**



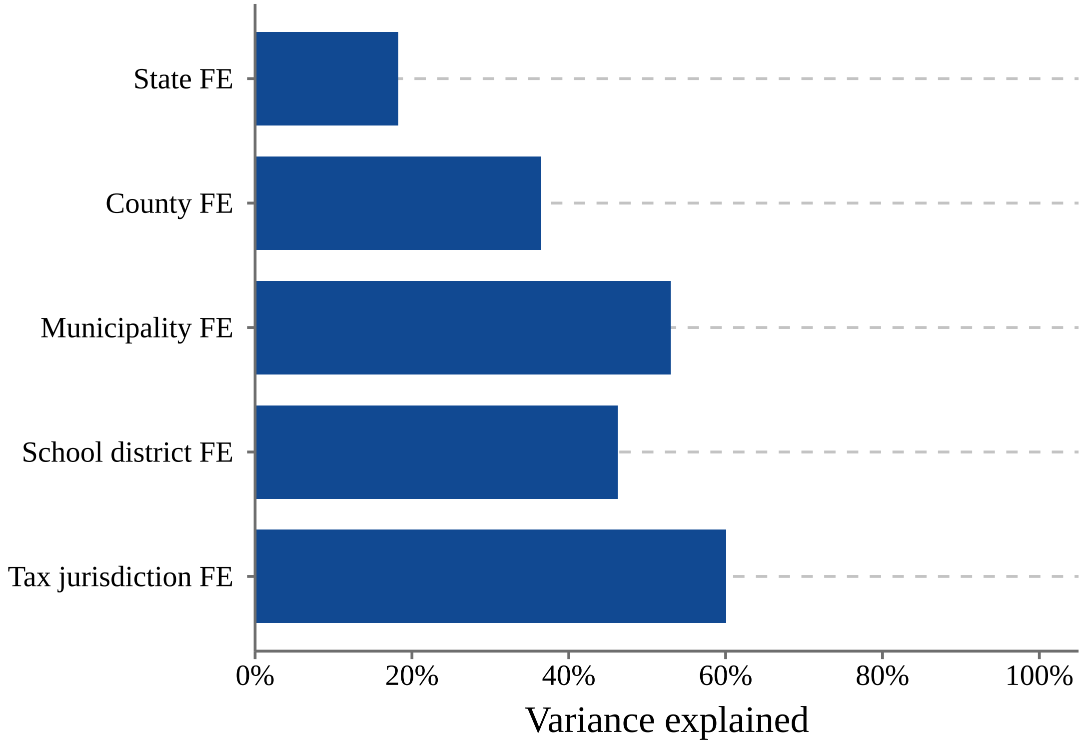
Note: This figure presents median property value to sale price ratio for transacted residential properties from 2007 to 2020. Ratios are calculated using property values from the current year and sale prices from the previous year, since property values are restrospective; e.g., ratios in 2007 are calculated using property values from 2007 and sale prices from 2006. The shaded band reflects the 25th and 75th percentile ratio.

Figure A.2: **Distribution of commercial property tax rates, 2021**



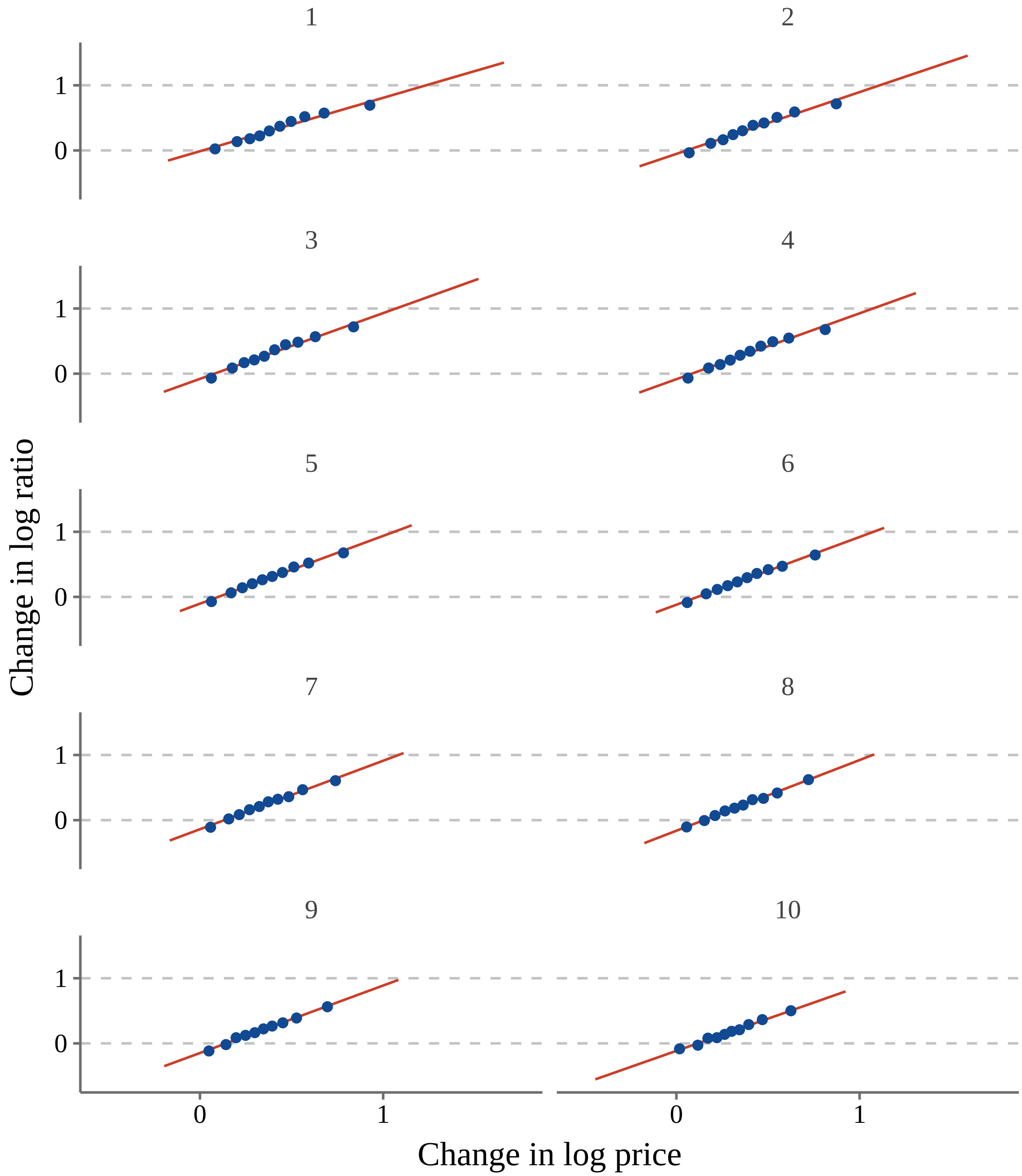
Note: Panel A of this figure presents the distribution of median commercial property tax rates in 2021 aggregated at the state level. Panel B of this figure presents the distribution of commercial property tax rates in 2021 after residualizing by state-specific median values.

Figure A.3: **Variance decomposition of commercial property tax rates, 2019**



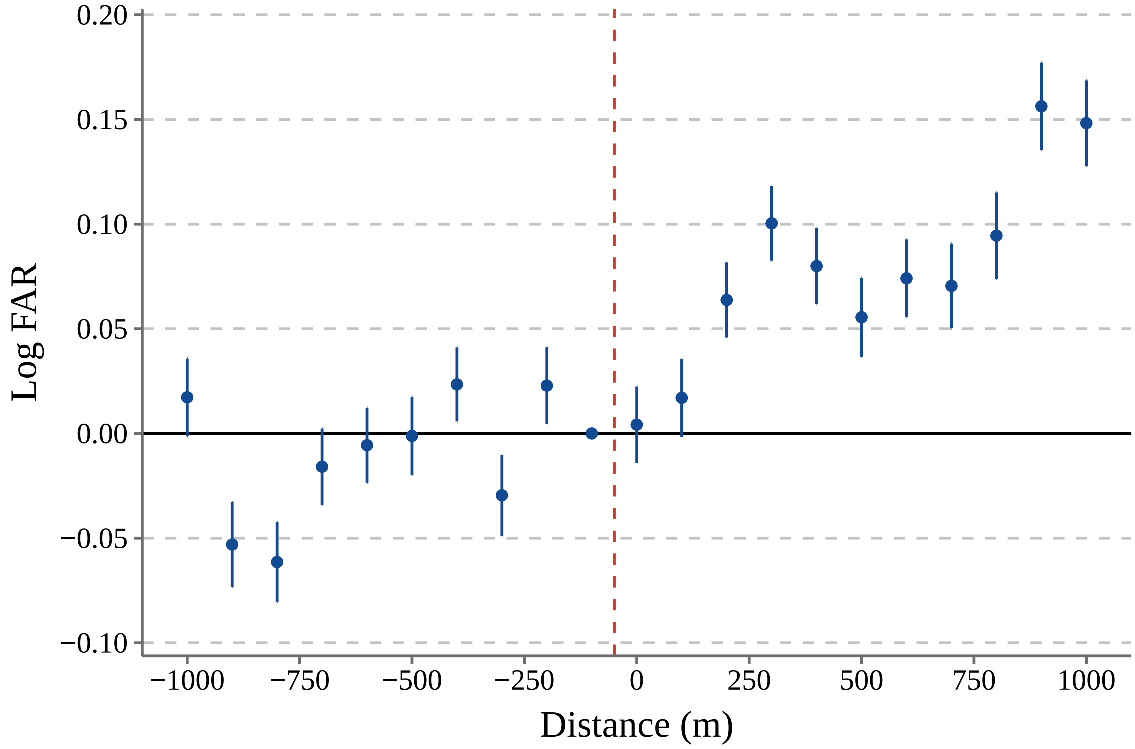
Note: This figure presents the proportion of variation in commercial property tax rates explained by different levels of government in 2019. Tax jurisdiction refers to the specific combination of county, municipality, and special districts to which a parcel belongs.

Figure A.4: **Binscatter of changes in housing expenditure share and changes in housing price by income decile, 2010–2019**



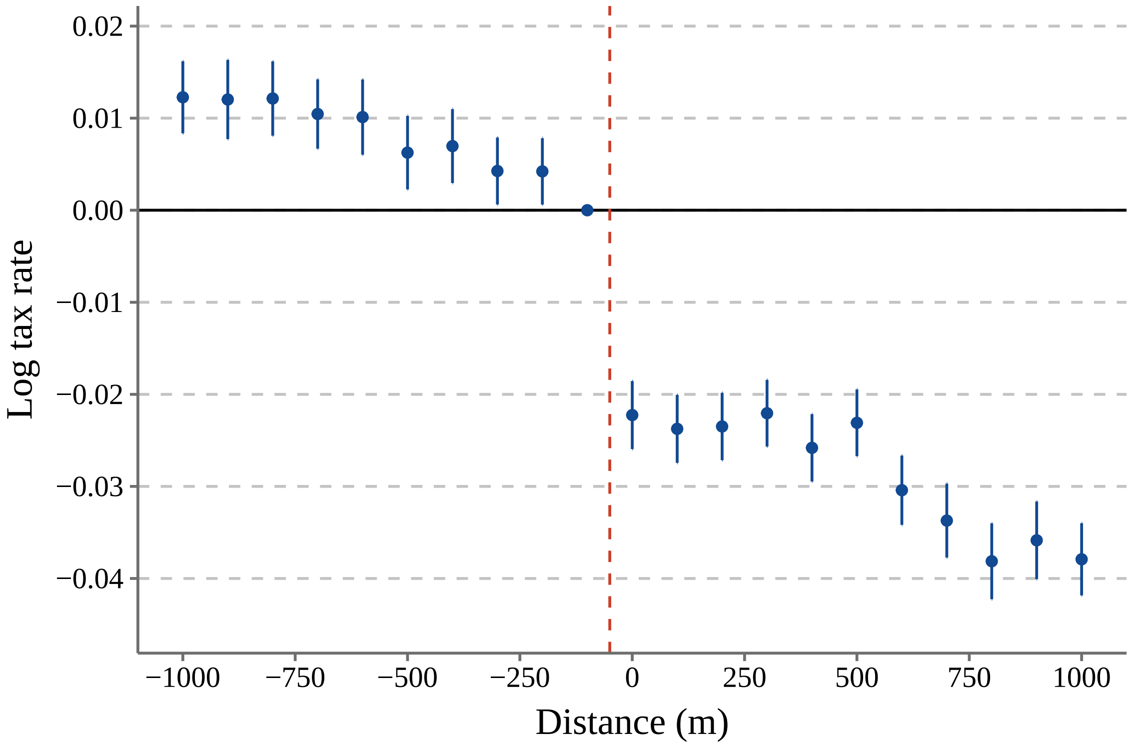
Note: This figure presents a binscatter analysis of changes in log housing expenditure share and changes in log housing price by income decile in 2019. Observations are at the ZIP code-level.

Figure A.5: **Border discontinuity with school district boundaries, 2019**



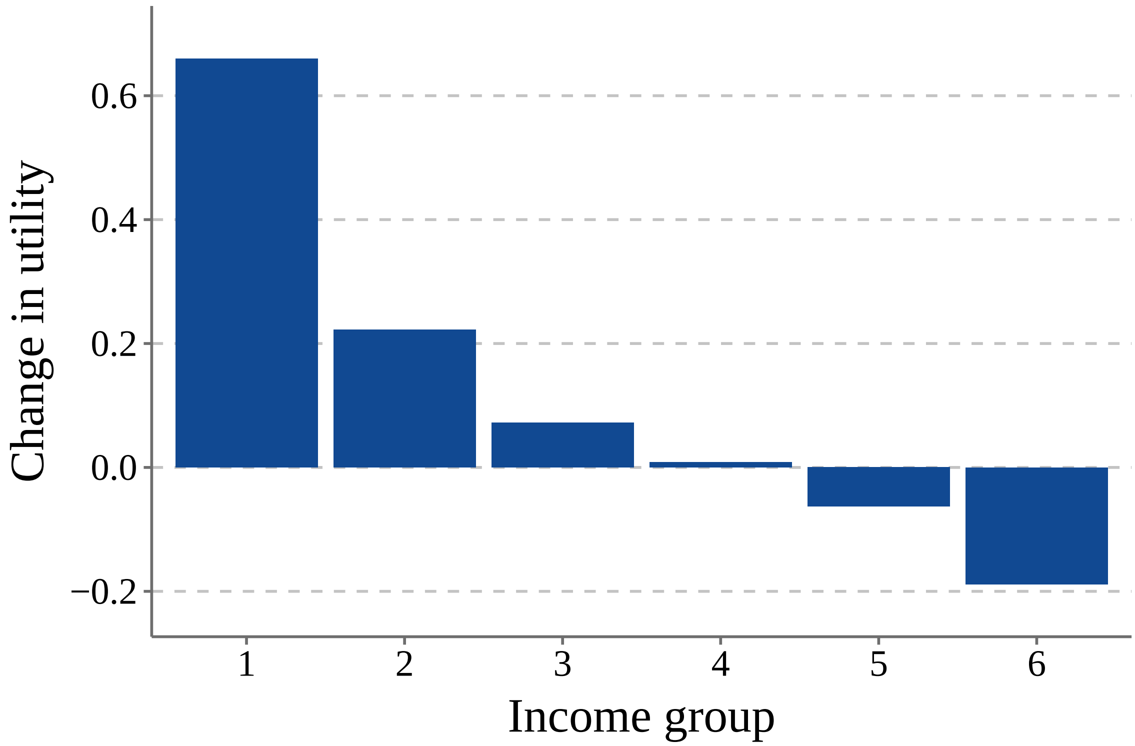
Note: This figure presents the coefficients from equation (8), without including interaction terms for housing supply elasticity. The outcome is parcel-level floor area ratio. Housing sales with a positive distance are located in school districts with higher test scores. Only school district boundaries within the same municipality are included. Standard errors are clustered by school district boundary.

Figure A.6: **Border discontinuity with school district boundaries, 2019**



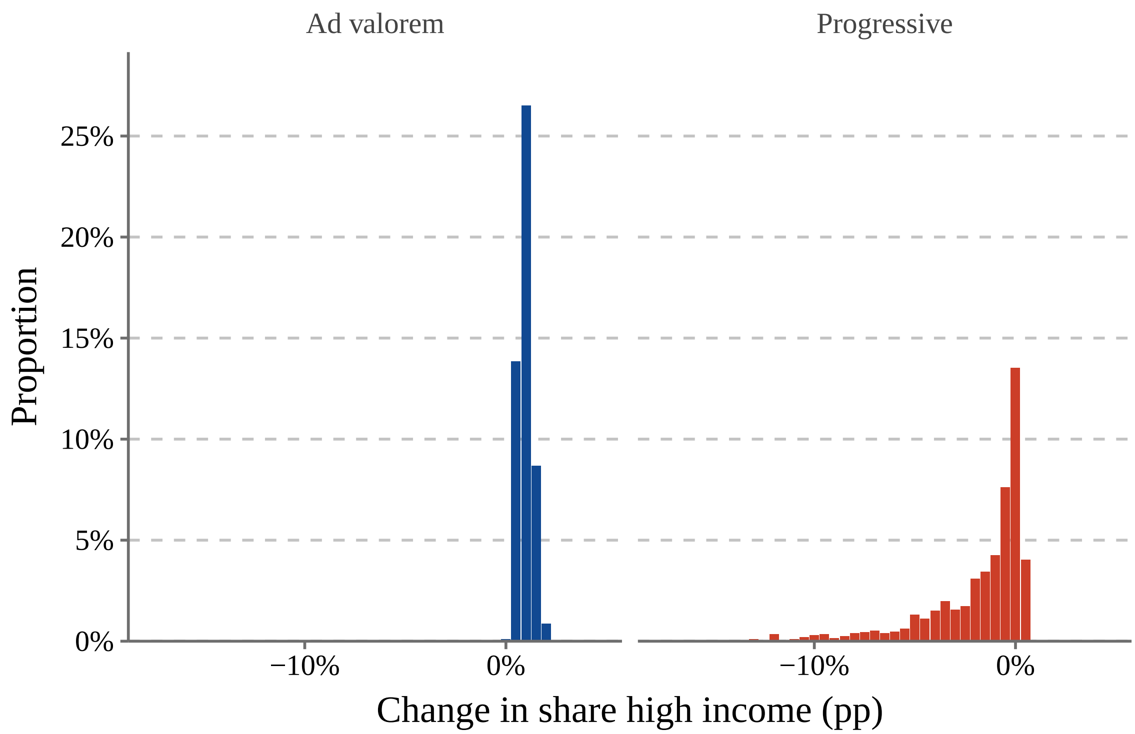
Note: This figure presents the coefficients from equation (8), without including interaction terms for housing supply elasticity. The outcome is parcel-level property tax rates. Housing sales with a positive distance are located in school districts with higher test scores. Only school district boundaries within the same municipality are included. Standard errors are clustered by school district boundary.

Figure A.7: **Welfare effect by income group: head tax, 2019**



Note: This figure presents the welfare effects of switching from head taxes to ad valorem property taxes in utility. 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 A.8: **High-income households migration under partial progressive property taxes**

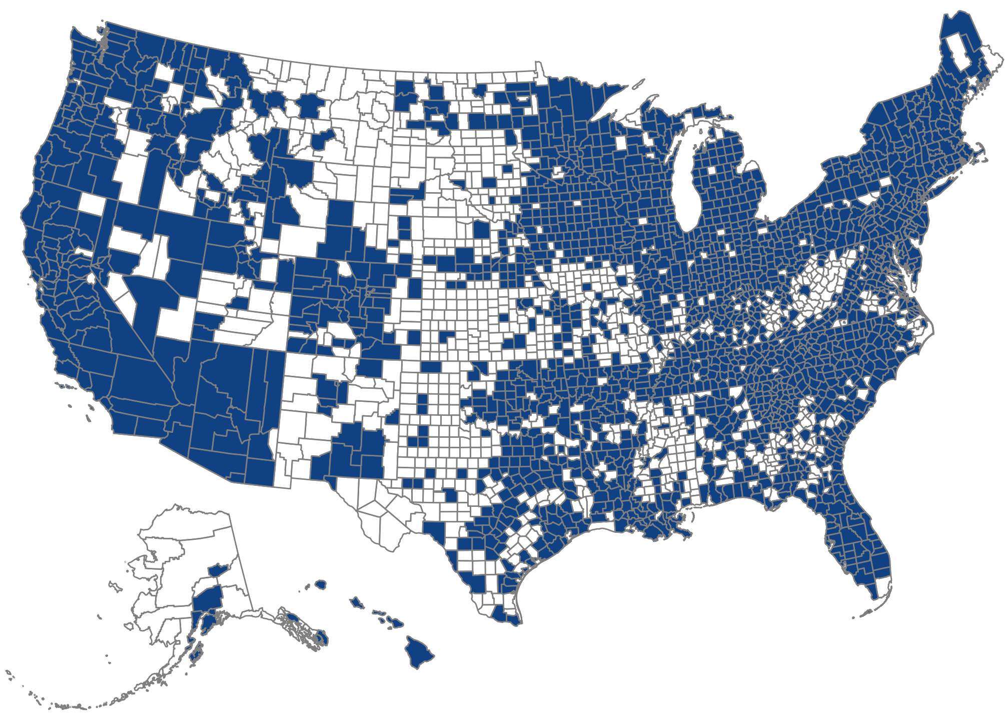


Note: This figure presents the distribution of changes in neighborhood-level share high-income ($200,000 or more) for neighborhoods that stay under an ad valorem property tax regime versus switch to a progressive property tax regime.

B Sample statistics

I restrict my analysis sample to counties with: (1) transaction and tax assessment records dating back to at least 2010; and (2) a minimum of 1,000 transactions from 2010 to 2019. Counties in my sample include 94% percent of the U.S. population: counties excluded from my sample are predominantly rural counties with low population density. Appendix Figure A.9 provides a map of the counties in my sample, and Appendix Table A.1 provides sample statistics on the counties using data from the 2019 American Community Survey. Counties in my sample are highly representative of the national population. When simulating household welfare under alternative tax regimes, I further 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.[52]

Figure A.9: **Map of counties in analysis sample**



Note: This figure presents a map of U.S. counties in my analysis sample.

[52]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.

Table A.1: **Sample statistics, 2019: American Community Survey**

	n	**Mean**	**Std. dev.**
All counties			
Population	3,220	101,868	327,345
Median income	3,220	\$52,648	\$14,990
Analysis counties			
Population	2,070	148,659.3	396,001
Median incom	2,070	\$56,305	\$14,583
Analysis counties, excluding CA			
Population	2,015	133,227.9	302,863
Median income	2,015	\$55,972	\$14,253

C Corelogic–HMDA merge

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.[53]

C.1 CoreLogic Deeds

In order to merge the CoreLogic Deeds data with publicly available HMDA data, I first clean and standardize the following variables in both datasets: census tract (using the 2000, 2010, and 2020 tract definitions as appropriate), year of loan application, mortgage purpose (i.e., purchase or refinance), mortgage type (i.e., conventional or other), mortgage amount, and lender name. I use these six variables to match mortgages in CoreLogic Deeds with mortgages in HMDA.

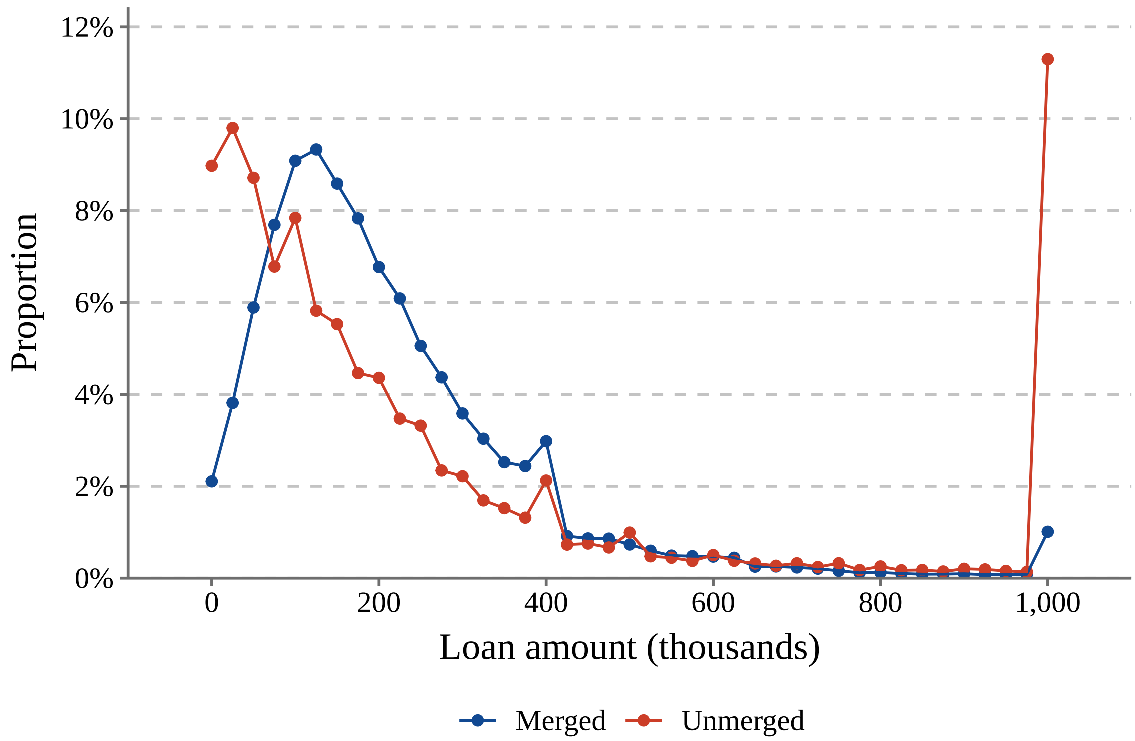
Second, I join the CoreLogic Deeds and HMDA datasets in four rounds. In the first round, I require matches on all six variables, where census tract, year of mortgage application, mortgage purpose, amd mortgage type must match exactly. I round the mortgage amount in CoreLogic Deeds using the same rounding rules as HMDA (i.e., to the nearest $1,000 prior to 2017 and to the nearest $5,000 after 2017) and this rounded mortgage amount must also match exactly. To match lender names in CoreLogic and HMDA, I compare the first word of each name. For example, if the lender name was "WELLS FARGO HM MTG INC", I would compare using the word "WELLS". If loans match one-to-one, I include such loans in my analysis sample; if there are multiple matches, I exclude such loans from my analysis sample. I remove matched loans from the CoreLogic Deeds and HMDA datasets and then attempt to rematch. In the following rounds, I relax the matching requirements. In the second round, I require a match on census tract, year of mortgage application, mortgage amount, and lender name. In the third round, I require a match on census tract, year of mortgage application, mortgage purpose, mortgage, type, and mortgage amount. In the fourth round, I require a match on census tract, mortgage amount, and mortgage year.

Compared to previous CoreLogic–HMDA crosswalks in the literature, I take a conservative approach to ensure the validity of the income measure for households in my sample. My overall match rate, mortgages in CoreLogic Deeds for which I find a unique match in HMDA, is 59,780,459 out of 106,965,725 mortgages, or 55.9%. Of these 59,780,459 matches, 74.2% are matched in round 1–meaning that mortgages match on all six variables. Omitting unmatched mortgages reduces my sample but does not impact my empirical analysis, provided that unmatched

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

mortgages are not systematically different from matched mortgages. Appendix Figure A.10) presents the distribution of loan amount for matched versus unmatched mortgages. Unmatched mortgages are more likely to have outlier loan amounts (i.e., loan amounts that are unrealistically small or unrealistically large), explaining why they remain unmatched.

Figure A.10: **Mortgage loan amount, 2010–2019: matched versus unmatched**



Note: This figure presents distributions of loan amounts in CoreLogic for mortgages from 2010 to 2019 that can be matched to a loan application in Home Mortgage Disclosure Act versus mortgages that cannot be matched.

C.2 CoreLogic Historical Property Taxation

I additionally combine 2019 property tax assessments from the Corelogic Historical Property Taxation data with publicly available HMDA data. To merge the two datasets, I use the CoreLogic–HMDA crosswalk described in Section C.1. Specifically, for a given property in 2019, I look for its most recent transaction from 2010 to 2019.[54] Transactions that are associated with a mortgage can then be matched to a loan application using my CoreLogic–HMDA crosswalk in order to obtain information about household income. I use the Consumer Price Index to adjust household income so that income is consistently measured in 2019 dollars. Of the 136,625,139 residential parcels with 2019 property tax assessments, I can obtain household income for 46,289,783 parcels, or 33.9%.

[54] A homeowner that purchases a house in 2019 in responsible for paying property taxes in 2019.

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. 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 2019 American Community Survey. This reweighting ensures that my empirical analysis is representative of the national population.

D Supplementary datasets

To facilitate my analysis of housing consumption and property taxation in the U.S., I compile fiscal, demographic, employment, and price data at various geographical levels using the following supplementary datasets.

The Census of Governments. The Census of Governments is an annual survey of local and state governments in the U.S. conducted by the U.S. Census Bureau since 1970. It provides detailed information on revenues, expenditures, and debt for local and state governments. I use the Census of Government to measure the extent to which local governments raise revenue through property taxes compared to other revenue sources such as sales taxes or business taxes. When measuring revenue, I exclude charges from public hospitals, as such charges are direct payments for medical services.

National Center for Education Statistics. The National Center for Education Statistics is a database of enrollment and financial measures for U.S. school districts since 1987. I use the National Center for Education Statistics to measure K-12 educational quality such as average expenditure per capita and average teacher to student ratios.

Stanford Education Data Archive. The Stanford Education Data Archive is a database of standardized test outcomes for school districts in the U.S from 2009 to 2019. I use the average school grade and cohort-adjusted standardized test score pooled across all subjects for a given school district.

Consumer Expenditure Survey. The Consumer Expenditure Survey is a quarterly interview of U.S. households conducted by the U.S. Bureau of Labor Statistics since 1980. Used to construct the Consumer Price Index, the Consumer Expenditure Survey surveys a nationally representative sample of households on their expenditures, income, and demographic characteristics. To calculate housing expenditure shares by income, I aggregate spending on shelter and utilities, fuels, and public services. Notably, I exclude spending on household operations, housekeeping supplies, and houshold furnishing and equipments.

Individual Income Tax Statistics. The Individual Income Tax Statistics from the Internal Revenue Service is a tabulation of individual income tax returns in the U.S. It provides income distributions and household characteristics for ZIP codes since 1990. The Individual Income Tax Statistics excludes households that do not file income tax returns, though the vast majority of households file an income tax return Langetieg, Payne, and Plumley (2017). I aggregate income distributions from a ZIP code level to a school district level using the Geocorr crosswalk from the Missouri Census Data Center.

American Comunity Survey. The American Community Survey has been annually conducted by the U.S. Census Bureau since 2005 and collects socioeconomic data (e.g., education, employment, and income) from approximately 1% of the U.S. population. In particular, I use the Supplementary Poverty Measure, which combines pre-tax household income from the America Community Survey with the TAXSIM calculator from the National Bureau of Economic Research to measure post-tax household resources. I use empirical moments from the Supplementary Poverty Measure to convert income distributions from the Individual Income Tax Statistics into post-tax distributions of household resources.

Infutor Data Solutions. Infutor Data Solutions is a database that records the entire address history for more than 300 million U.S. residents. Infutor is a data aggregator of address data using many sources including phone books, magazine subscriptions, and credit header files. This data was first described and made use of by Diamond, McQuade, and Qian (2019) to study household migration. I follow the data processing methodology in Diamond, McQuade, and Qian (2019) to construct school district-level migration flows in 2019.

2000 U.S. Census of Population. I use journey to work and place of work tabulations from the 2000 U.S. Census of Population, which measure household commuting flows by industry at the census tract level. Using the Geocorr crosswalk from the Missouri Census Data Center, I aggregate industry employment shares from a census tract level to a ZIP code level. I measure industry employment shares using location of household residence, as opposed to location of household workplace.

Quarterly Census of Employment and Wages. The Quarterly Census of Employment and Wages reports quarterly measures of U.S. employment and wages by industry at a county level and has been conducted by the U.S. Bureau of Labor Statistics since 1980. I use the Quarterly Census of Employment and Wages to construct Bartik labor demand shocks. In particular, I interact ZIP code level industry employment shares in 2000–from the 2000 U.S. Census of Population–with national changes in employment by industry from 2010 to 2019–from the Quarterly Census of Employment and Wages. Industry is defined at a 2-digit NAICS code.

Card, Rothstein, and Yi (2025). Card, Rothstein, and Yi (2025) provides causal estimates for the effects of location on earnings. I interpret the effects of location on earnings as measures of total factor productivity.

Zillow Housing Data. Zillow Housing Data provides typical home values and market rents for U.S. ZIP codes. Typical home values and market rents are provided for different housing types (e.g., single-family versus condos) and housing quality (e.g., homes in the 5th to 35th percentile range versus homes in the 65th to 95th percentile range). I calculate annual metropolitan area-level price-to-rent ratios using Zillow Housing Data on median prices and rents for single-family homes. For each metropolitan area and year, I divide median prices for single-family homes by median rents for single-family homes to get a price-to-rent ratio.

Nielsen Homescan Panel. Launched in 2004, the Nielsen Homescan Panel is a nationally representative longitudinal survey in which participating U.S. households record their purchases of groceries and consumer packaged goods (e.g., snacks and personal care products). Households additionally respond with demographic characteristics, such as their income and their ZIP code of residence. To construct ZIP code-level price indices for non-housing consumption, I run the regression:

$$p_{it} = \lambda_{z_i t} + \gamma_{it} + \varepsilon_{it}$$

where p_{it} is the price of good i in year t, $\lambda_{z_i t}$ is a fixed effect for ZIP code-year, and γ_{it} is a fixed effect for product-year. I define a product by its Universal Product Code (UPC).

Baum-Snow and Han (2024). Baum-Snow and Han (2024) provides causal estimates of housing supply elasticities for census tracts. Estimates of housing supply elasticities from Baum-Snow and Han (2024) are provided at the census-tract level. I aggregate housing supply elasticities to a municipality level and a school district level following the recommended methodology in Baum-Snow and Han (2024).

E Household heterogeneity

In my model in Section 4, household type refers to households of different income groups. I find that household income is a sufficient statistic for housing consumption. Specifically, using the 2019 American Community Survey, I estimate the following regression equation:

$$\log(y_i) = \alpha + \beta \log(w_i) + \gamma X_i + \varepsilon_i$$

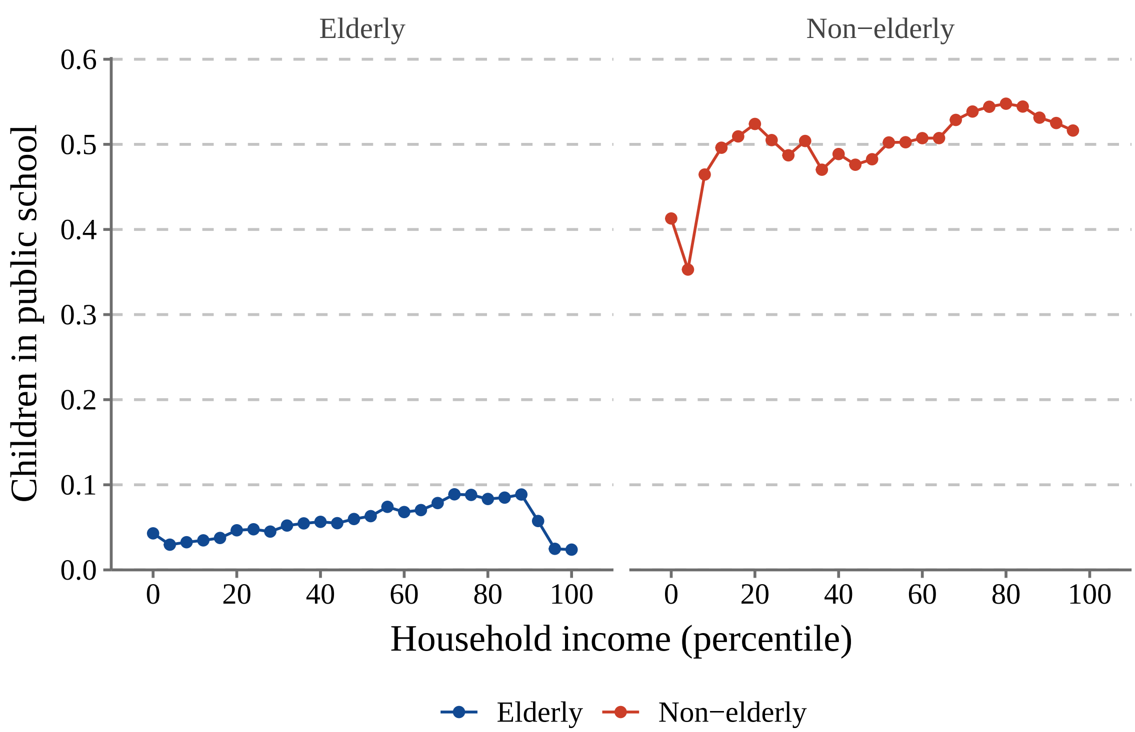
where y_i is a measure of housing consumption for household i (e.g., market value of property of residence), w_i is annual household income, and δX_{it} are other demographic covariates (i.e., household size, number of school-aged children in household, and age of head of household). Appendix Table A.2 presents results: annual household income explains 19.1% of the variation in housing consumption (as measured by the market value of property of residence), whereas additionally including demographic covariates only increases the variation explained by 0.3%.

To assess whether it is a reasonable assumption that the fiscal cost of an additional household is homogenous by household type, I plot the average number of children attending K-12 public school per household by household income using the 2019 American Community Survey (Appendix Figure A.11). Number of children attending K-12 public school is a good proxy for the fiscal cost of an additional household since the majority of property taxes collected are used to fund K-12 public schools. I find that the average number of children attending K-12 public school per houshold is increasing by household income. However, this relationship is primarily driven by households where the head of household is elderly (i.e., age 65 or older)–such households are typically lower income and have no children in the household. Controlling for whether the head of household is elderly, there is no statistically significant relationship between the average number of children attending K-12 public school per household and household income.

Table A.2: **Sample statistics, 2019: American Community Survey**

	Market value		**Property tax**		**Rent**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\beta \log(w_i)$	0.464	0.460	0.464	0.459	0.281	0.261
	(0.001)	(0.052)	(0.001)	(0.045)	(0.001)	(0.006)
Covariates		X		X		X
R^2	0.191	0.194	0.152	0.154	0.255	0.274
n	562,158	562,158	562,158	562,158	255,148	255,148

Figure A.11: Average number of children attending K-12 public schools per household, 2019



Notes: This figure presents the average number of children attending K-12 public school per household by household income and age of head of hosuehold.

F Model with non-linear taxes

I extend the model in Section 4 to allow local governments to use non-linear taxes. In particular, local governments can implement increasing marginal tax rates, where the amount of housing consumption before a threshold is taxed at one rate, and the amount after is taxed at another rate.[55] The model with non-linear taxes differs from the model in Section 4 in two ways.

F.1 Housing demand

Assume a unit measure of heterogeneous households, where households differ according to their type θ. 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}; high-quality housing h_{Hj}, which has a price r_{Hj}; and a non-housing good c_j, which has a price p_j. The amount of total housing consumed by the household is taxed at rate τ_{1j} before threshold k_j and rate τ_{2j} after the threshold. 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:

$$\begin{aligned} w_\theta - T_j = \ & \mathbb{I}\left(rh_j \leq \frac{k_j}{1+\tau_{1j}}\right) rh_j\left(1+\tau_{1j}\right) + \\ & \mathbb{I}\left(rh_j > \frac{k_j}{1+\tau_{1j}}\right)\left[k_j + \left(rh_j - \frac{k_j}{1+\tau_{1j}}\right)\left(1+\tau_{2j}\right)\right] + p_jc_j \end{aligned}$$

where:

$$rh_j = r_{Hj}h_{Hj} + r_{Lj}h_{Lj}$$

Each household's optimized housing consumption is therefore one of the following, depending on whether they choose to consume prior to the threshold, at the threshold, or after the threshold:

[55] The District of Columbia became the first municipality in the U.S. to implement increasing marginal tax rates on property in 2024. Residential property is taxed at 0.85% of its value up to $2,500,000 and 1% of the value exceeding $2,500,000. Countries such as Mexico, South Korea, and Denmark have progressive property tax systems with increasing marginal tax rates on property.

$$rh_j^* = \begin{cases} w_\theta \frac{\alpha_\theta^\eta \alpha_j^\eta \tilde{r}_{\theta j}^{1-\eta}\left(1+\tau_{1j}\right)^{-\eta}}{\alpha_\theta^\eta \alpha_j^\eta \tilde{r}_{\theta j}^{1-\eta}\left(1+\tau_{1j}\right)^{1-\eta}+p_j^{1-\eta}} & \text{if } rh_j^* < \frac{k}{1+\tau_{1j}} \\ \frac{k}{1+\tau_{1j}} & \text{if } rh_j^* = \frac{k}{1+\tau_{1j}} \\ \left(w_\theta - k\left(1-\frac{1+\tau_{2j}}{1+\tau_{1k}}\right)\right) \frac{\alpha_\theta^\eta \alpha_j^\eta \tilde{r}_{\theta j}^{1-\eta}\left(1+\tau_{2j}\right)^{-\eta}}{\alpha_\theta^\eta \alpha_j^\eta \tilde{r}_{\theta j}^{1-\eta}\left(1+\tau_{2j}\right)^{1-\eta}+p_j^{1-\eta}} & \text{if } rh_j^* > \frac{k}{1+\tau_{1j}} \end{cases}$$

where:

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

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

$$r_{Lj}h_{Lj}^* = \delta_{\theta j} rh_j^*$$
$$r_{Hj}h_{Hj}^* = \left(1-\delta_{\theta j}\right) rh_j^*$$

F.2 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 a non-linear tax on housing consumption, where housing consumption is taxed at rate τ_{1j} before threshold k_j and rate τ_{2j} after the threshold. Notably, we make two assumptions: first, the fiscal cost of an additional household is homogenous by household type. Second, the fiscal cost of an additional household is constant.

Local prices $\left(r_{jL}, r_{jH}\right)$ and taxes $\left(T_j, \tau_{1j}, \tau_{2j}, k_j\right)$ 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 $rh_{\theta j}^*$ as the expenditure function for housing for a household of type θ in neighborhood j given optimized utility. 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:

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

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

$$
\begin{aligned}
MC_j = & \sum_{\theta} \left(\frac{N_{\theta j}}{\sum_{\theta} N_{\theta j}} \mathbb{I} \left(rh^*_{\theta j} \leq \frac{k}{1+\tau_{1j}} \right) rh^*_{\theta j} \tau_{1j} \right) + \\
& \sum_{\theta} \left[\frac{N_{\theta j}}{\sum_{\theta} N_{\theta j}} \mathbb{I} \left(rh^*_{\theta j} > \frac{k}{1+\tau_{1j}} \right) \left(\frac{k}{1+\tau_{1j}} \tau_{1j} + \left(rh^*_{\theta j} - \frac{k}{1+\tau_{1j}} \right) \tau_{2j} \right) \right] + T_j
\end{aligned}
$$

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