The Redistributive and Efficiency Effects of Property Taxation*

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Abstract

Property taxes raise revenue proportional to housing values, thereby distorting housing consumption and creating unequal tax burdens for households receiving the same public services. This paper develops a spatial equilibrium model to quantify the redistributive and efficiency effects of property taxation. I use household microdata to estimate housing demand: the price elasticity of housing expenditures is 0.54, 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 2.4%, but decreases equity and increases income segregation. Under a property tax system, low-income households receive implicit transfers of approximately $1,500 annually, whereas high-income households pay $4,000. 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 $650 billion in tax revenue for state and local governments in 2022. In fact, 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 Governments 2022). 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 a consumption-distorting form of non-benefit taxation.[1] In particular, property taxes function as a commodity 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. This redistribution distorts location choice, since the taxes paid by households no longer correspond to the cost of providing public services to households. The magnitude of economic inefficiency generated by property taxes and the equity implications of such taxes 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 U.S. dataset that enables observation of housing consumption and property tax burdens across household demographic groups from 2007 to 2021. 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 from the Census Bureau 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 U.S. property taxation, including the spatial distribution of property tax rates and measures of nominal intrajurisdictional redistribution. I highlight three facts in particular. One, property taxes exhibit large interstate and intrastate heterogeneity. States differ widely in their reliance on property taxes, with

[1] Under benefit taxation, households pay proportional to their consumption of public goods. Benefit taxation mimics the efficiency of competitive markets. As Oates (1972) argues: "Since the tax-price paid by the consumer reflects accurately the cost of the public goods he consumes, this system of finance introduces no incentives for inefficient behaviour." A standard result in public finance theory is that local governments should refrain from non-benefit taxation of mobile economic units (Oates, 1999).

median effective tax rates in 2021 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 approximately 12.5% higher in neighborhoods closer to central business districts, implying differentiation in public services consistent with Tiebout (1956).

Two, higher property tax rates are correlated with lower housing consumption, suggesting the presence of excess burden. Controlling for household income and housing prices, households in tax jurisdictions with a 75th-percentile effective property tax rate (2.0%) purchased houses that were approximately 4.7% smaller in square footage than households in jurisdictions at the 25th percentile (1.0%) in 2021. This difference in housing size offers evidence that property taxes distort household consumption decisions.

Three, 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 paid $1,000 less in property taxes than the average household in their jurisdiction in 2021. In contrast, households in the top quartile of income paid $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 a rivalrous, 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. Accordingly, 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 neighborhoods in response to changes in housing prices.

I use household revealed preferences to estimate model parameters that govern the intensive margin of housing demand. To address housing price endogeneity, I leverage the observability of household income to construct a novel instrument. Identification relies on

[2] I define a neighborhood as an elementary or unified K-12 school district. In the U.S., school districts can independently levy property taxes, and the majority of revenue raised from property taxes is used to fund elementary and secondary education. K-12 education is an excludable public good since households may only attend a school district if they live within the geographical boundary of the district.

the assumption that holding a given household's income fixed, changes in the income distribution of other households in the same neighborhood have no demand spillovers on the given household's preferences (Berry and Haile, 2016). I estimate that the elasticity of housing expenditure with respect to housing prices is 0.54 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, Ioannides and Ngai Forthcoming). Preferences for housing are also non-homothetic, with higher-income households consuming less housing as a share of total expenditure.

On the extensive margin of housing demand, I estimate that households have a migration elasticity of 2.4 with respect to housing prices. I use a border discontinuity design that leverages the interaction between variation in local public goods and variation in housing supply elasticities for identification. Furthermore, I use gross migration flows to estimate the model parameter that governs household substitution patterns, i.e., where households choose to move conditional on outmigration. I find that households prefer to move within rather than across commuting zones.

Finally, I use my model to simulate household welfare in 2021 under alternative tax regimes. I consider four tax regimes: (1) ad valorem property taxes; (2) head taxes; (3) progressive property taxes implemented by a centralized government; and (4) progressive property taxes implemented by decentralized local governments.[3] Counterfactual simulations reveal important tradeoffs between equity and efficiency. Compared to head taxes—a non-distortionary benchmark—ad valorem property taxes provide \$1,500 in implicit transfers to low-income households (i.e., households that earn less than \$25,000) annually while high-income households (i.e., households that earn more than \$200,000) pay \$4,000 more.[4] Replacing ad valorem property taxes with head taxes eliminates deadweight loss and increases housing supply by 2.4%, but amplifies income segregation across neighborhoods.

Conversely, progressive property taxes implemented by a centralized government are more equitable than ad valorem property taxes, but at the cost of further distorting housing consumption. For instance, adopting a universal increasing marginal tax rate system similar to that of Denmark would increase implicit payments from high-income households by \$3,900, allowing for an additional \$300 in transfers to low-income households.[5] Income segregation

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

[4] Head taxes are lump-sum taxes that impose a fixed per-capita charge for residing in a given neighborhood. In the Tiebout (1956) model, the workhorse model of local public finance, free mobility of households results in head taxes being a form of benefit taxation. California is the only state in the U.S. that levies lump-sum taxes on property.

[5] In Denmark, residential property is taxed at 0.51% of its value up to DKK 9,200,000 and 1.4% of the

is reduced across neighborhoods, but housing supply decreases by 0.8%. Redistribution is significantly limited by high-income household mobility when progressive property taxes are not implemented universally. When only individual local governments adopt progressive property taxes in a decentralized system, high-income households "vote with their feet" and migrate to avoid redistribution, thereby amplifying income segregation.

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 use household revealed preferences to *empirically* quantify the magnitude of the inefficiency relative to the equity gains through redistribution.[6]

Furthermore, existing empirical work on property taxes is often constrained to a limited sample of municipalities due to lack of centralized assessment data (see Zodrow (2023) for a review). A notable exception is Avenancio-León and Howard (2022), who use a national dataset to demonstrate how county assessor offices typically overvalue housing located in low-income, minority neighborhoods. I use a comprehensive national sample to provide novel, stylized facts on the spatial distribution of property taxes and their incidence by income, addressing a significant gap in our understanding of how property tax burdens vary geographically and demographically.

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

value exceeding DKK 9,200,000. That is, the marginal tax rate nearly triples when property values exceed the threshold.

[6] An adjacent, but complementary literature studies the optimal provision of local public goods (e.g., Cellini, Ferreira, and Rothstein 2010; Löffler and Siegloch 2021; Biasi, Lafortune, and Schönholzer 2025). This paper abstracts away from whether local governments are providing the optimal quantity of local public goods. It instead answers the question of *how* local governments should raise revenue.

linear property taxes and allowing for heterogeneous preferences for housing variety.

Lastly, this paper contributes to the vast literature on commodity taxation. In particular, property taxes can be viewed as a form of commodity 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 distributional incidence of commodity 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.[7] If the transaction is associated with a mortgage, CoreLogic additionally provides detailed information about the loan, including: loan amount, loan type, and name of the lender who originated the loan. I limit my sample to transactions classified as arms-length (i.e., between unfamiliar buyers and sellers) and properties that are sold individually as opposed to a portfolio sale.

The Corelogic Historical Property Taxation dataset contains property tax assessments for

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

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 B.1 provides a map of the counties in my sample, and Appendix Table B.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.[8]

To geolocate each housing transaction and property tax assessment, I rely on the Nationwide Parcel Boundary map from Regrid.[9] 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.[10]

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.[11] 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

[8] 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). While there exist other states with property tax limitations, limitations are significantly more permissive than California. Consequently, California is the only state in the U.S. that separately uses a lump-sum parcel tax system to raise local government revenue.

[9] Regrid is a data aggregator of parcel characteristics and directly sources parcel maps from county governments.

[10] 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.

[11] 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.

with CoreLogic data.

I follow a similar procedure in Bayer et al. (2022) to merge CoreLogic data and HMDA data. The CoreLogic and HMDA merge uses a multi-step algorithm that matches 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 55.9% 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 C.1), 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 Governments, 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.[12] Infutor Data Solutions is a database that records the entire address history for more than 300 million U.S. residents.[13]

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.[14] 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. Appendix Figure C.2 presents the distribution of household income in 2019 in the 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

[12] 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.

[13] 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.

[14] 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).

who recently purchased their house with a mortgage.[15]

I find that the distribution of household income in my sample largely matches the distribution of household income for homeowners that recently purchased their house with a mortgage, suggesting that the income measures in the HMDA data are reasonably reliable.[16] 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. Appendix Figure A.1 presents the sources of local government revenue from 1970 to 2022 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 $650 billion of state and local property taxes were collected in 2022, 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 2022 Census of Governments, at least 47.7% of property taxes collected by local governments were allocated to K-12 school districts.[17]

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 ju-

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

[16] Mortgage lenders will typically verify an applicant's income and employment by requesting documents such as paycheck stubs, tax returns, and bank statements. Mortgage lenders are incentivized to accurately assess income since mortgage payment-to-income ratios are an important predictor of loan default.

[17] In 2022, 47.7% of property taxes collected by local governments were directly allocated to independent K-12 school districts. However, 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 budgeted to those school districts, meaning 47.7% is an underestimate for the share of property taxes allocated to K-12 school districts.

risdiction, 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.[18] Assessment ratios, typically established by state legislatures, are used to convert property values into assessment values.

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

3.2 Stylized facts about property taxes

I document novel stylized facts about local property taxation, which provide the empirical foundations for the spatial equilibrium model.

3.2.1 Variation in property tax rates

First, property tax rates are highly heterogenous, demonstrating both significant interstate and intrametrapolitan variation. Panel A of Figure 1 presents the distribution of median residential property tax rates aggregated at the state level in 2021. Panel B of Figure 1 depicts the distribution of residential property tax rates after residualizing by state-specific median values, thereby isolating within-state variation.[19] 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.

To examine spatial patterns within metropolitan areas, Figure 2 presents a binscatter analysis correlating residential property tax rates with percentile of distance from the nearest central business district using assessments in 2021.[20] Notably, the percentile of distance

[18] 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.2 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.

[19] Appendix Figure A.3 presents interstate and intrastate distributions of commercial property tax rates.

[20] I define as a central business district the collection of census tracts categorized as business districts in

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 for parcels 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 12.5% higher than average.

Substantial intrastate and intrametropolitan 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. Appendix Figure A.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.[21] 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.[22] Hence, to a first order approximation, property taxes can be characterized as an ad valorem tax with the tax rate set by school districts.

To empirically verify the above characterization, I conduct the following variance decomposition: I run separate regressions of parcel-level property tax rates on different levels of government and calculate the variance in property tax rates explained by each level. That is, I estimate 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 2021 and λ_{g_i} is a fixed effect for a given level of government (e.g., county, municipality, school district). Appendix Figure A.5 presents the results of those regressions.[23] Approximately 86% of variation in property tax rates are explained by school district fixed effects whereas 87% of variation in residential

the 1982 Census of Retail Trade. Results are qualitatively similar using alternative definitions of central business districts (e.g., location of city halls).

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

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

[23] Appendix Figure A.6 repeats the same variance decomposition exercise, but for commercial parcels.

property tax rates are explained by tax jurisdiction fixed effects.[24] For model simplicity, I consequently define local governments as K-12 school districts.

3.2.2 Property tax rate dynamics

Second, local governments dynamically 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 stayed consistent from 2007 to 2021. Figure 3 presents house price, property value, tax rate, and tax amount indices from 2007 to 2021. To construct the house price index, I follow the repeat sales methodology from Case and Shiller (1987).[25] To construct the 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.[26] Local governments typically hold legislative sessions where legislators use anticipated property values provided by county assessor's offices to determine property tax rates that meet a desired revenue level. Therefore, I model local governments as endogenously setting property tax rates to satisfy an exogenous revenue requirement.

3.2.3 Evidence of deadweight loss

Third, higher property tax rates are correlated with lower housing consumption, suggesting the presence of deadweight loss. Figure 4 presents a residualized binscatter analysis correlating housing square footage purchased with local property tax rates using transactions in 2021. Local property tax rates are defined as the median residential rate within each transaction's school district. The binscatter analysis includes residualizations for log household income and log housing prices, measured as the log price per square foot of the transaction. Controlling for household income and housing prices, households in tax jurisdictions with a 75th-percentile effective property rate (corresponding to a rate of 2.0%) purchase houses

[24] 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.

[25] In particular, I run the regression $y_{it} = \gamma_i + \lambda_t + \varepsilon_{it}$, where y_i is the log sale amount for residential parcel i in year t, γ_i are parcel fixed effects, and λ_t are year fixed effects.

[26] 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.

that are approximately 4.7% smaller in square footage than households in tax jurisdictions at the 25th percentile (corresponding to a rate of 1.0%). Property taxes thus function as a consumption tax on housing, distorting consumption away from housing to other goods. Standard economic theory predicts that the magnitude of the excess burden depends on the price elasticities of housing demand and supply.

3.2.4 Nominal intrajurisdictional redistribution

Finally, 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 average tax amount paid by households in the same school district. Specifically, for each parcel for which I observe household income, I first residualize its 2021 tax payment by the average 2021 tax payment in its school district. I then estimate the regression equation:

$$y_i - \overline{y}_{s_i} = \lambda_{w_i} + \epsilon_i \tag{1}$$

where y_i is the tax payment for parcel i in 2021, s_i is the school district that parcel i belongs to, and λ_{w_i} are household income percentile fixed effects.[27] Figure 5 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.[28]

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:

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

[28] This is less progressive than state income taxes. According to the 2019 American Community Survey, households in the bottom quartile of income pay $2,500 less in state income taxes than the average household in their state. In contrast, households in the top quartile of income pay $4,900 more in state income taxes than the average household in their state.

$$y_i = \gamma_{s_i} + \lambda_{w_i} + \epsilon_i \tag{2}$$

where y_i is an outcome for transaction i in 2021, γ_{s_i} are school district fixed effects, and λ_{w_i} are household income group fixed effects. Figure 5 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.

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 comprehensively study the welfare effects of property taxes, I develop a spatial equilibrium 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.[29]

4.1 Housing demand

Assume a unit measure of heterogeneous households, where households differ according to their type θ.[30] 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 $w_{\theta j}$ and locally consume: low-quality housing h_{Lj}, which has a price

[29] 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 E.

[30] For empirical implementation, household types are defined by household income. Descriptive evidence suggests that household income is a sufficient statistic for housing demand. For example, controlling for household income, there is no economically significant relationship between household size and housing demand. Appendix F provides more detail.

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 housing consumption. The parameters $\alpha_\theta \alpha_j$ govern the neighborhood-specific *appeal* of housing relative to non-housing consumption for type θ households.[31] Heterogeneity in the taste and appeal parameters across type allow households to implictly have non-homothetic preferences for housing consumption. Heterogeneity in the taste and appeal parameters across neighborhoods capture unobserved differences in housing variety between neighborhoods.

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:

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

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

[31] I assume log-additive separability by type in the neighborhood-specific appeal of housing; i.e., $\log(\alpha_{\theta j}) = \log(\alpha_\theta) + \log(\alpha_j)$. I directly test and fail to reject this assumption in the data. For example, Figure 8 provides descriptive evidence validating the assumption.

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:

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

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

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

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 provided is dependent on their type:

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

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

$$F(K_j, B_jL_j) = B_jL_jf\left(\frac{K_j}{B_jL_j}\right)$$

where K_j and L_j refer to total (non-land) capital and labor, respectively and B_j is the local productivity level. Cost of capital is fixed at ρ and output is sold on a national market for a price of one. Firms equates their marginal product of capital to the cost of capital, meaning:

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

The marginal product of labor is then:

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

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.[32] 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.[33]

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

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

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

[32] Since I define household type as income and local government revenue is primarily used to fund K-12 education, this assumption is equivalent to assuming that there is no within-neighborhood correlation between household income and number of children attending public school. Among households where the head is a working-age adult, number of children attending public school is relatively constant by household income. Appendix F explores an extension of the model where the marginal cost of providing amentities to households is heterogeneous by household type.

[33] 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.

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

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 the model in Section 4 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 (e.g., Albouy, Ehrlich, and Liu (2016)), I use price-to-rent ratios to impute owners' equivalent rent from house prices. 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.[34] I then use my imputed owners' equivalent rent from house prices to estimate housing expenditure shares by income group, where I proxy for total expenditure with income.[35] As a validation exercise, I benchmark expenditure shares calculated using transactions in 2019 to expenditure shares calculated using the 2019 Consumer Expenditure Survey. I find that housing expenditure shares are

[34] 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). Diamond and Diamond (2024) estimates price-to-rent ratios using properties in the American Housing Survey that switch occupancy status from owner-occupied to rental-occupied and vice versa.

[35] Property taxes are paid by landlords, not renters—however, standard economic theory predicts passthrough of property taxes to rent prices. Therefore, my imputed owners' equivalent rent reflect net rent prices (i.e., rent prices inclusive of property taxes).

relatively similar across the two sources, except for very low-income households (Appendix Figure A.7).[36]

Housing taste. In the 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 for type θ households. 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 with an average price of \$7.5 per square feet, it must be the case that such households spend one-third of their housing expenditure on low-quality housing and two-thirds on high-quality housing.[37] Therefore, I would estimate a taste parameter of $\delta_{\theta j} = 1/3$ for households of type θ in neighborhood j. Notably, identifying the parameter $\delta_{\theta j}$ requires ex-ante defining low- versus high-quality housing, where the choice of definition is a scale normalization. Since the parameter $\delta_{\theta j}$ is neighborhood-specific, definitions of low- versus high-quality housing are also specific to the neighborhood. Heterogeneity in the taste parameter across neighborhoods capture unobserved quality differences in housing varieties between neighborhoods.

I estimate annual neighborhood-level taste parameters using property tax assessments, where neighborhood is defined as a ZIP code.[38] 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.[39]

[36] Since I use income as a proxy for total expenditure, my calculated housing expenditure shares are mechanically inflated for households with little income due to division by near zero. Expenditure shares calculated using the 2019 Consumer Expenditure Shares use actual total expenditure, which is typically higher than income for very low-income households (e.g., due to in-kind transfers).

[37] Consuming housing with an average price of \$7.5 per square feet suggests that the household consumes equal quantities of low-quality and high-quality housing. Since high-quality is twice as expensive, the household spends two-thirds of its housing expenditure on high-quality housing.

[38] For counterfactual simulations, I additionally estimate annual neighborhood-level taste parameters where neighborhood is defined as a school district instead.

[39] 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 for a given neighborhood. 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

Figure 7 presents the distribution of $\delta_{\theta j}$ by ZIP code that I estimate for each income group in 2019. I find that higher 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 the parameter $\delta_{\theta j}$ 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 (i.e., P_{Lj} and P_{Hj}):[40]

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

where PTR_j is the price-to-rent ratio and τ_j is the rental tax rate.[41]

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. To estimate the elasticity of substitution, 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:

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

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 $\tilde{r}_{\theta j}$

market values for all properties (Appendix Figure A.2).

[40]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.

[41]Assume houses are priced via discounted cash flow $P = \frac{1}{\rho}\left(r - Pt\right)$, where P is house price, r is net rent price, t is the property tax rate, and ρ is the discount rate. Gross rents (i.e., rents exclusive of property taxes) are implicitly taxed at rental tax rate $\tau = \frac{P}{r}t$.

following equation (3). To measure changes in the price of non-housing consumption p_j, I construct price indices using the Nielsen Homescan data.[42] 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.[43] Therefore, I estimate the parameter η using a combination of 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 $\Delta \log(\tilde{r}_{\theta j})$ are correlated with changes in the appeal of housing $\Delta \log(\alpha_j)$. For example, neighborhoods with higher housing prices may also have more modern, and thus more desirable, houses. Appendix Figure A.8 presents a binscatter analysis correlating changes in log housing expenditure shares with changes in log housing prices from 2010 to 2019, with observations at the ZIP code-income decile level. Without price endogeneity, the estimated slope from a least squares regression would identify the parameter η.[44]

To address price endogeneity, I instrument for changes in rent prices with ZIP-code level Bartik labor demand shocks $Bartik_j$.[45] I make the identification assumption that local labor demand shocks are uncorrelated with changes in neighborhood-specific appeal of housing $\Delta \log(\alpha_j)$. 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 viola-

[42] 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.

[43] 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.

[44] Appendix Figure A.9 repeats the binscatter analysis correlating changes in log housing expenditure shares with changes in log housing prices from 2010 to 2019 by income deciles. Estimated slopes from a least squares regression are similar across income deciles, confirming homogeneity in the parameter η across income.

[45] 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 and employment shares are calculated using households' place of residence.

tion, since I directly observe income and control for non-homothetic preferences for housing with income decile fixed effects. As an alternative interpretation, my instrument is similar in spirit to Waldfogel instruments where I leverage the observability of household incomes (Berry and Haile, 2016). For a given household, changes in the income distribution of other households in their neighborhood affect housing prices through income effects. Therefore, the exclusion restriction is valid if holding a given household's income fixed, changes in the income distribution of other households in their neighborhood have no demand spillovers on their preferences. 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.[46]

Therefore, my estimating equation is:

$$\begin{aligned}\Delta \log\left(\frac{S_{\theta j}}{1-S_{\theta j}}\right) &= \beta_1 \Delta \widehat{\log\left(\tilde{r}_{\theta j}\right)} + \beta_2 \Delta \log\left(1+\tau_j\right) + \\ &\quad \beta_3 \Delta \log\left(p_j\right) + \lambda_\theta + \gamma_{c_j} + \epsilon_{\theta j} \\ \Delta \widehat{\log\left(\tilde{r}_{\theta j}\right)} &= Bartik_j + \gamma_1 \Delta \log\left(1+\tau_j\right) + \\ &\quad \gamma_2 \Delta \log\left(p_j\right) + \lambda_\theta + \gamma_{c_j} + \epsilon'_{\theta j}\end{aligned} \tag{5}$$

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.[47]

Table 1 presents the results of regressions corresponding to equation (5). My preferred specification (Column 4) produces an estimate of 0.27 for the parameter η, which implies an elasticity of housing expenditure share with respect to price of 0.54. I therefore empirically reject a common assumption in the literature that households have unit elastic demand for housing.[48] I instead find that housing demand is relatively price inelastic. Notably, my

[46] 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. The quality of the U.S. housing stock appears to have changed very little from 2010 to 2019 (Appendix G).

[47] Results are noisier, but similar without weighting ZIP codes by their population in the 2010 Decennial Census.

[48] Prominent exceptions of literature that do not assume unit elastic demand for housing are reviewed in

elasticity estimates are similar in magnitude to previous estimates in the literature.[49]

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. Heterogeneity in the parameter α_j allows preferences for housing consumption to be non-homothetic, whereas heterogeneity in the parameter α_j captures unobserved differences in housing variety between neighborhoods. To estimate the appeal parameters, suppose that we observe housing expenditure share $S_{\theta j}$ for income group θ in neighborhood j. From the 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 from housing expenditure shares. My estimating equation is thus:

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

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 $\eta\log\left(\alpha_\theta\right)$, whereas ZIP code fixed effects identify $(1-\eta)\log\left(p_j\right) + \eta\log\left(\alpha_j\right)$.[50] To bring the reduced form equation (6) to data, I set $\eta = 0.27$ as estimated in Column 4 of Table 1.

Figure 8 presents a cross-sectional binscatter correlating log relative housing expenditure

Gaubert and Robert-Nicoud (2025) and Ioannides and Ngai Forthcoming.

[49]To my best knowledge, Albouy, Ehrlich, and Liu (2016) and Finlay and Williams (2022), with respective estimates of 0.51 and 0.48 for the elasticity of housing expenditure share with respect to price, are 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. Finlay and Williams (2022) also estimates the elasticity using cross-sectional differences in housing expenditures share, but instruments for housing prices using Saiz (2010)'s measures of regulatory and geographical constraints on housing construction. However, areas with constrained housing supply generally have an older and less desirable housing stock, a violation of the exclusion restriction.

[50]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 in all neighborhoods to $p_j = 1$. For counterfactual simulations, I additionally estimate annual neighborhood-level taste parameters where neighborhood is defined as a school district instead.

shares with log net rent 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 the parameter α_θ, whereas average deviations from a slope of $(1-\eta)$ identify the 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 the model in Section 4, the extensive margin of housing demand is crucially governed by the parameter σ, which characterizes the dispersion of household idiosyncratic preferences for neighborhoods. Intuitively, the parameter can be interpreted as a measure of household mobility. Larger values of the parameter σ suggest that households are less sensitive to housing prices when choosing a neighborhood for residence.

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 prices respond to exogenous demand shocks is dependent on housing supply elasticities (e.g., Saiz (2010)). In the extreme, when housing supply is perfectly elastic, demand shocks affect only quantity and not price. Therefore, comparing housing 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 in a given neighborhood is characterized by the equation:

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

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 standard economic theory, exogenous changes in local public goods have no effect on housing prices when housing supply is perfectly elastic since:

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

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.[51] 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.[52] Crucially, I only compare houses across school district borders within the same municipality, ensuring similarity in non-education local public goods.[53] 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.[54] The key identification assumption I make is that discrete changes in unobserved quality at school district borders within the same municipality are uncorrelated with discrete changes in housing supply elasticity (e.g., zoning).

In particular, I estimate the regression equation using property transactions from 2009

[51] 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.

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

[53] Figure A.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.

[54] 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).

to 2019:

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

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 9 presents the regression coefficients for $\boldsymbol{\beta}$ when estimating equation (8). In contrast, Appendix Figure A.10 presents the regression coefficients for $\boldsymbol{\beta}$ when estimating equation (8) without including interaction terms for housing supply elasticity:

$$\log\left(p_{it}\right) = \beta^{-1.0} \cdot \mathbb{I}\left(-1km \leq Dist_{it} < -0.9km\right) \times \Delta Test_{b_i} + \ \ldots \ + \\ \beta^{1.0} \cdot \mathbb{I}\left(1km \leq Dist_{it} < 1.1km\right) \times \Delta Test_{b_i} + \\ \delta X_{it} + \lambda_{b_i t} + \epsilon_{it}$$

I find that a standard deviation increase in average school district test scores increases house prices by 7% 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 3% 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:

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

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 $\lambda_{b_i t}$ are border-year fixed effects. To operationalize equation (9), I set $\eta = 0.27$ as estimated in Table 1 and calibrate $E[S] = 0.25$ 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 $\sigma^{-1} = 9.8$, which can be approximately translated to households having a share outmigration elasticity of 2.4 with respect to housing prices.[55]

Migration patterns. Finally, I estimate the distribution parameters for ε_{ij}, which characterizes household idiosyncratic preferences for neighborhoods. Intuitively, the distribution of ε_{ij} governs household migration patterns; i.e., where a household chooses to relocate given outmigration. I assume that household idiosyncratic preferences are distributed generalized extreme value, consistent with a two-level nested logit model in which households first choose a commuting zone, then choose a school district within the commuting zone for residence. 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:

$$\varepsilon_{ijt} = \xi_{iC_j} + \lambda_2 \left(\xi_{ij} + \lambda_1 \xi_{ijt}\right) \tag{10}$$

where ξ_{ijt}, $\xi_{ij} + \lambda_1 \xi_{ijt}$, and ε_{ijt} are all distributed standard Gumbel. Idiosyncratic preferences for school districts are therefore correlated both across time and within commuting zones. Appendix Figure A.11 graphically presents the implicit correlation structure for household idiosyncratic preferences. The parameter λ_1 governs the likelihood that a household chooses to move school districts in any given year, whereas the parameter λ_2 governs where households choose to move.[56]

Notably, the marginal distribution of idiosyncratic preferences in any given year is con-

[55] 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 are more idiosyncratic than preferences for metropolitan areas.

[56] For household idiosyncratic preferences to be consistent with rational utility maximization, it must be the case that λ_1 and λ_2 are bounded between 0 and 1. Loosely speaking, $1 - \lambda_1 \lambda_2$ can be interpreted as the correlation between idiosyncratic preferences across time, whereas $1 - \lambda_2$ can be interpreted as the correlation between idiosyncratic preferences over commuting zones.

sistent with a two-level nested logit with parameter λ_2, where school districts are nested within commuting zones. The population share for school district j in commuting zone C_j in year t is given by:

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

where v_{jt} is the *non-idiosyncratic* indirect utility derived by household i given residence in school district j in year t. Therefore, a value of λ_2 less than one 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.[57] 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 a smaller value of λ_1. Conditional on moving, if households typically move to new school districts in the same commuting zone, this suggests a smaller value of λ_2.

I estimate $\lambda_1 = 0.16$ (0.02) and $\lambda_2 = 0.39$ (0.04) via method of simulated moments, where I approximate the cumulative density functions of distributions ξ_{iC_j} and ξ_{ij} in equation (10) via Fourier inversion on the characteristic function of a standard Gumbel distribution. 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. Appendix Figure A.12 graphically presents the moment equations used to estimate the parameters of the generalized extreme value distribution. Between 2010 and 2019, only 13.6% of households outmigrated from their original school district; of those households, the majority (55.8%) relocated within the same commuting zone. That is, households are unlikely to move school districts in any given year and conditional on moving school districts, households prefer to move to a school district in the same commuting zone.

[57] For any given value of the parameter λ_2, a standard Berry (1994) inversion of changes in population shares uniquely identifies changes in v_{jt}.

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) progressive property taxes implemented by a centralized government; and (4) progressive property taxes implemented by decentralized local governments.

Head taxes, by virtue of their non-distortionary nature, offer a theoretically efficient benchmark for quantifying the redistributionary and efficiency effects of property taxes.[58] I assess progressive property taxes as a policy counterfactual, particularly given that the District of Columbia became the first U.S. municipality to implement increasing marginal tax rates on property in 2024. A common argument in the fiscal federalism literature is that local redistribution is difficult without coordination by local governments, since high-income households are mobile and can simply migrate to avoid redistribution (Oates, 1999). Therefore, I consider two progressive property tax regimes: universal implementation by a centralized government, and partial implementation by a subset of decentralized local governments.

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).[59] 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).[60] To get local governments' marginal cost per household, I calculate the average property tax burden per residential parcel for each neighborhood. The only remaining parameters I 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

[58]Head taxes are not consumption-distortive due to being lump-sum taxes. Since I assume that the marginal cost of providing amentities to household is homogenous by household type, head taxes are a form of benefit taxation.

[59]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 equally contribute to total housing supply elasticity for the neighborhood.

[60]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.

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.[61]

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.[62] 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. Appendix Figure A.13 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.

As an additional source of validation, I use my structural model to replicate Lutz (2015), which examines the housing price capitalization effect of an exogenous school finance reform in New Hampshire. Lutz (2015) finds that in suburban New Hampshire school districts, a 15% reduction in property tax burden—while maintaining school spending constant—resulted in a 5% increase in housing prices. To replicate Lutz (2015), I decrease the marginal cost of providing amenities to households in New Hampshire school districts by 15% while keeping neighborhood-specific amenities fixed. I find that housing prices increase in New Hampshire by an average of 4.5%, similar to Lutz (2015).

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 2.3% across neighborhoods (Figure 10), leading to a 2.4% increase in housing supply (Figure 11). 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 12). Segregation between lower-income households and higher-income households would increase by an average of 1 standard deviation as measured with a dissimilarity index, primarily

[61] 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.

[62] 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.2). I impute rental tax rates using property tax rates from 2019 property tax assessments following the procedure in Section 5.1.

because the elimination of property taxes would decrease the affordability of higher-income neighborhoods for lower-income households. Third, the efficiency gains of implementing a head tax would come at the cost of reducing equity. Relative to head taxes, low-income households (i.e., households that earn less than \$25,000) experiences a utility gain equivalent to \$1,500 in annual income under ad valorem property taxes, while high-income households (i.e., households that earn more than \$200,000) experience a utility loss equivalent to \$4,000 (Figure 13).

I then simulate counterfactual rents and tax rate for a universal progressive property tax system 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 0.9% across neighborhoods (Figure 10), leading to a 0.8% decrease in housing supply (Figure 11). The efficiency losses of implementing a universal progressive tax would come at the benefit of promoting equity. Relative to head taxes, the low-income households experience a utility gain equivalent to \$1,800 in annual income under universal progressive property taxes, while high-income households experience a utility loss equivalent to \$7,900 (Figure 14). Additionally, universal progressive taxes reduce income segregation (Figure 12).

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" by migrating to avoid redistribution, therefore amplifying income segregation instead. I simulate counterfactual rents and tax rates for a tax regime where the largest school district in each commuting zone adopts a progressive property tax system with increasing marginal tax rates, but all other school districts adopt an ad valorem property tax.[63] In the case where the marginal tax rate triples at the threshold, low-income households experience almost no additional redistribution relative to ad valorem taxes (Figure 15). Relative to head taxes, low-income households experience a utility gain equivalent to \$1,550 in annual income under partial progressive property taxes, while high-income households experience a utility loss equivalent to \$4,900 (Figure 15).[64]

[63] Therefore, progressive property taxes are implemented in school districts including one-third of all households.

[64] Appendix Figure A.14 plots migration by high-income households by whether a school district implements a progressive property tax. To avoid redistribution, high-income households migrate out of school

Finally, I examine which local governments are most successful at local redistribution if they were to independently implement progressive property taxes. To do so, I simulate counterfactual rents and tax rates for tax regimes where an individual school district adopts a progressive property tax system with increasing marginal tax rates, and all other school districts adopt an ad valorem property tax. I then correlate the welfare gains for low-income households if an individual school district implements progressive property taxes to demographic characteristics of the school district. Larger, wealthier school districts are the most successful at local redistribution, which are typically school districts located in urban centers (Appendix Figure A.15). Intuitively, larger school districts have more low-income households to redistribute to, whereas wealthier school districts have more high-income households to redistribute from.

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, generating approximately $650 billion in revenue for state and local governments in 2022. 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 an inefficient non-benefit tax.

This paper quantifies the welfare effects of local property taxation and evaluates the equity-efficiency tradeoff 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 12.5% higher in local governments closer to central business districts, suggesting differentiation in the local public goods offered. Second, higher property tax rates are correlated with lower housing consumption. Controlling for household income and housing prices, households buy 4.7% smaller houses for each percentage point increase in effective property tax rate. 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.

districts with progressive property taxes and migrate into school districts with ad valorem property taxes.

Next, I develop a spatial equilibrium model to quantify the welfare effects of property taxes. Notably, I estimate that the elasticity of housing expenditure with respect to price is 0.54, 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 of approximately \$1,500 annually, while high-income households pay \$4,000 more. Replacing property taxes with head taxes would increase housing supply by 2.4% through eliminating price distortions, but would 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, providing 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 migration.

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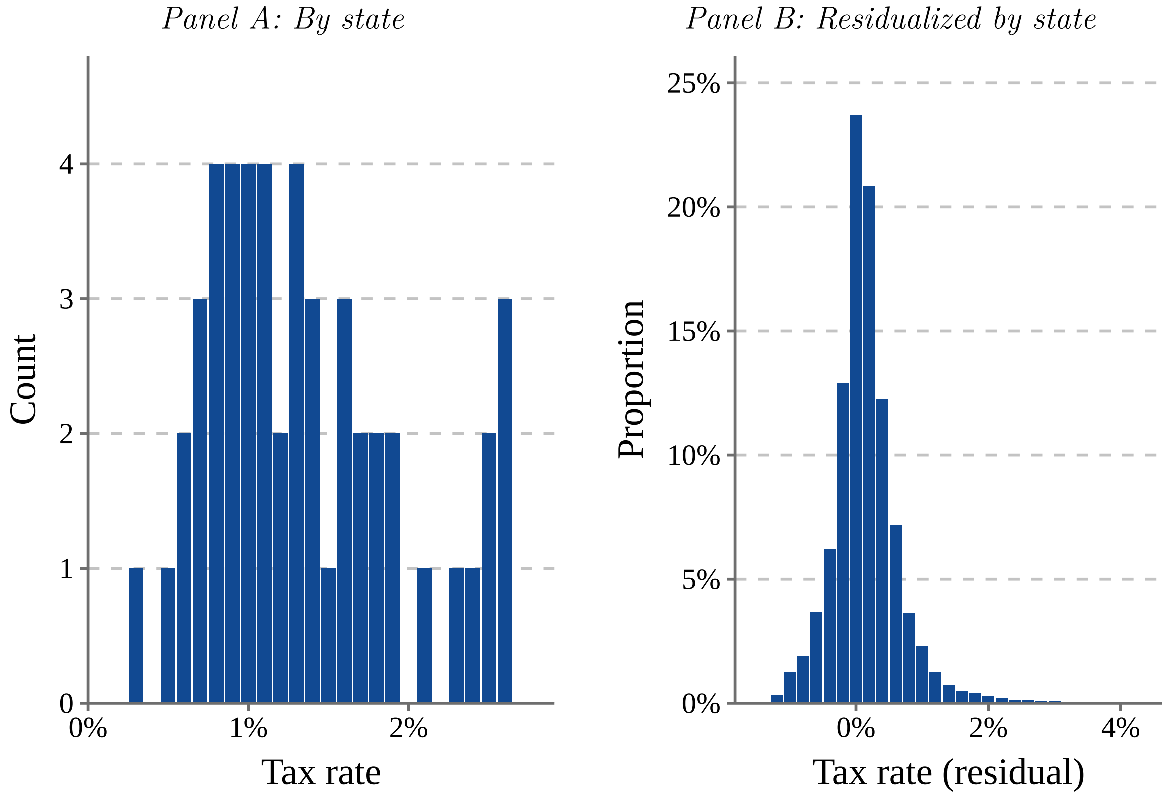
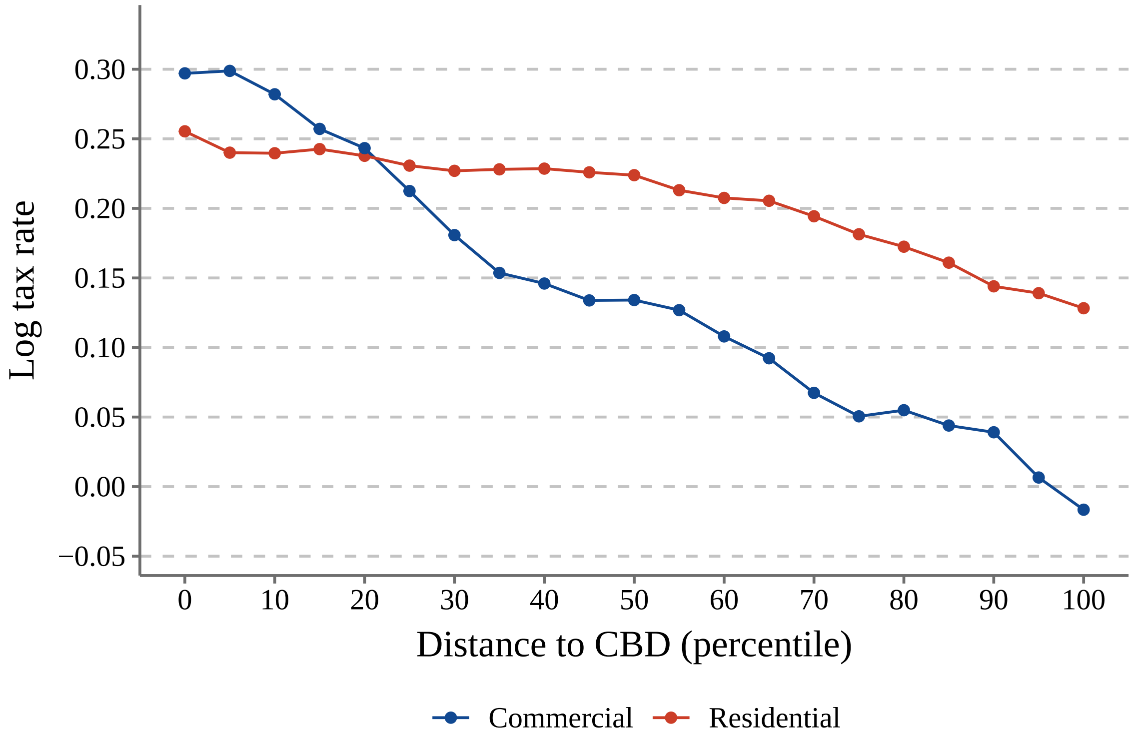
Figure 1: **Distribution of residential property tax rates, 2021**



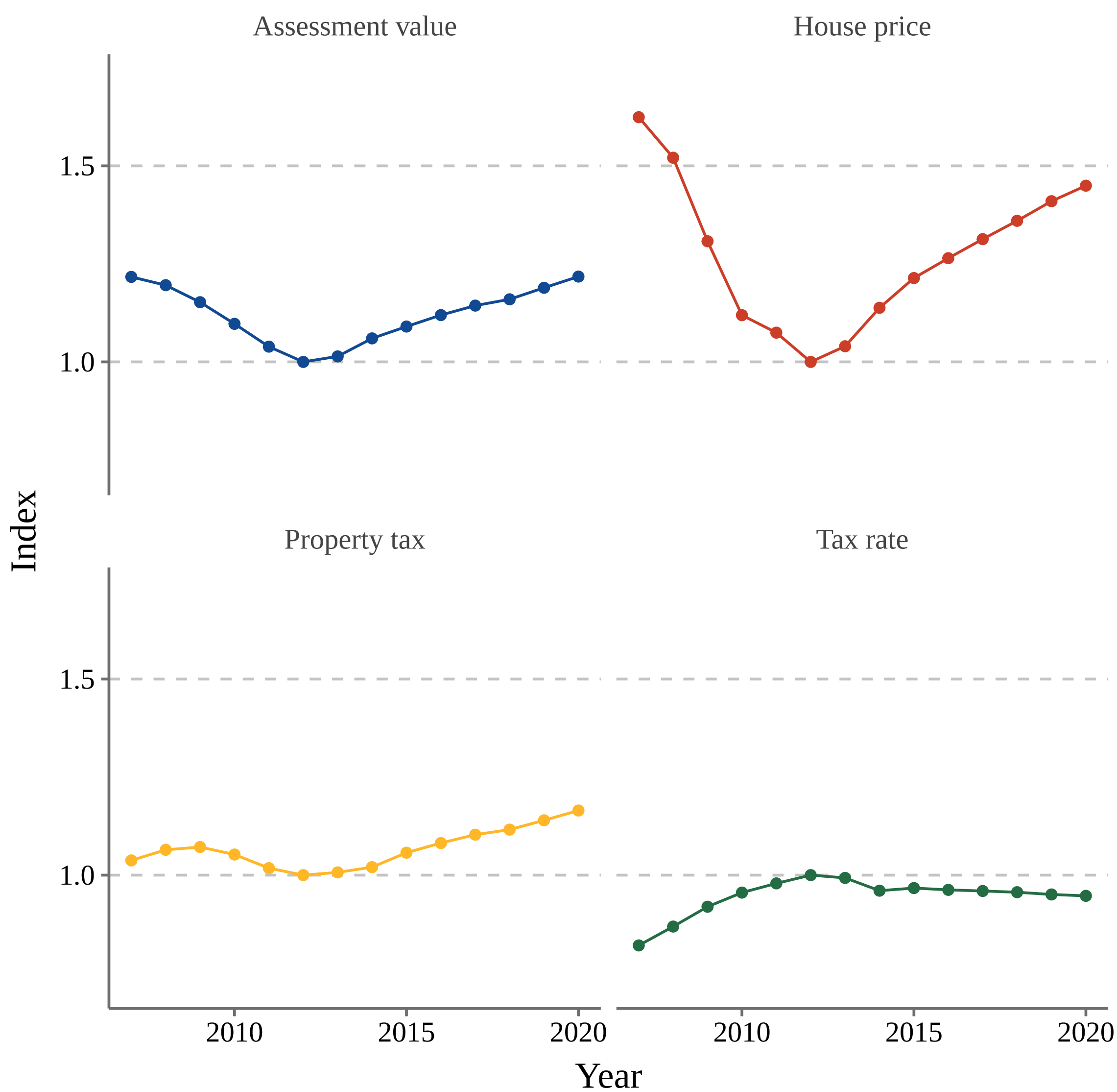
Note: Panel A of this figure presents the distribution of median residential property tax rates in 2021 aggregated at the state level. Panel B of this figure presents the distribution of residential property tax rates in 2021 after residualizing by state-specific median values.

Figure 2: **Binscatter of property tax rate by distance to central business district, 2021**



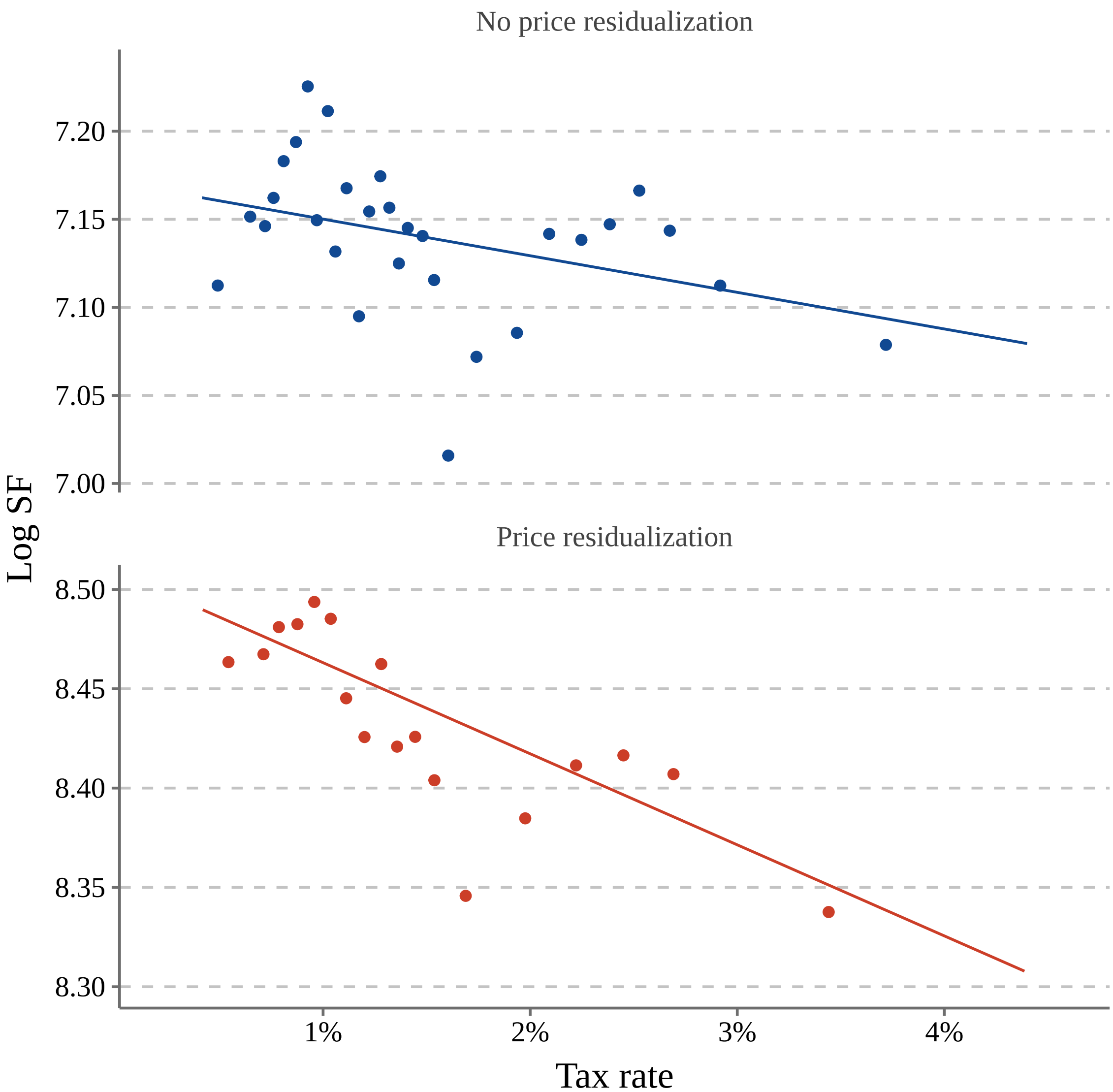
Note: This figure presents a binscatter analysis of log property tax rates by percentile of distance from the nearest central business district (CBD) using tax assessments in 2021. Percentile of distance from the nearest CBD is calculated relative to each metropolitan area, ensuring balanced representation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

Figure 3: **House price, property value, tax rate, and property tax amount indices, 2007–2021**



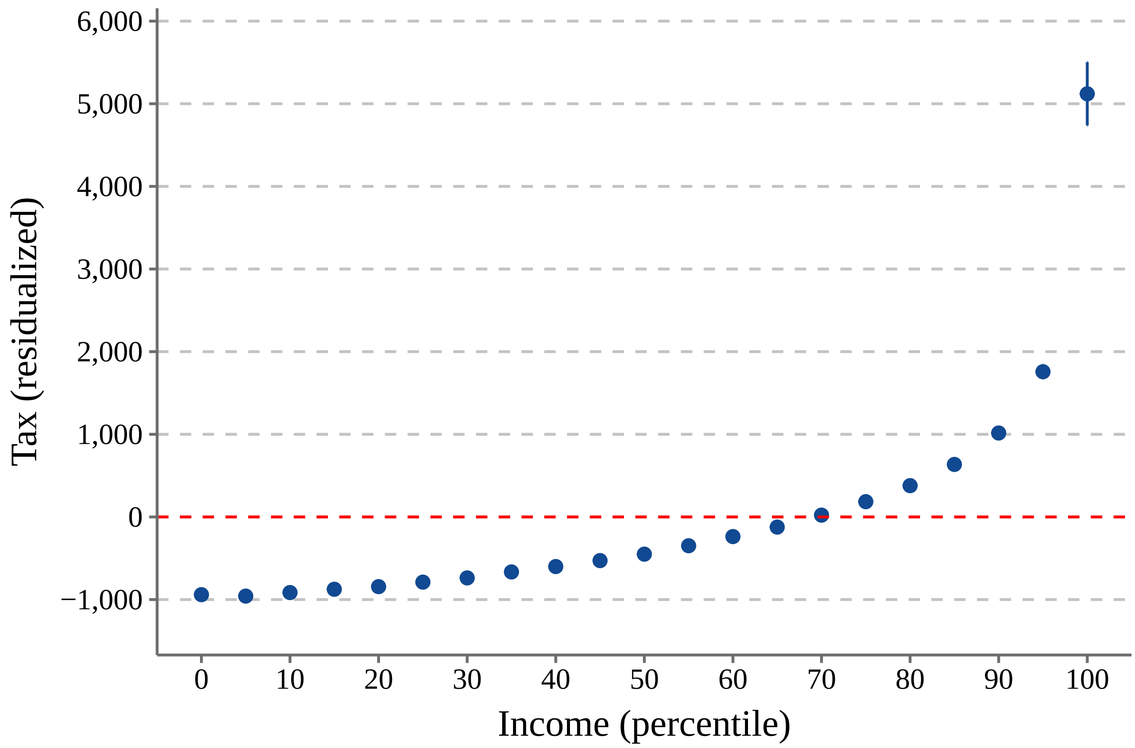
Note: This figure presents house price, property value, tax rate, and tax amount indices from 2007 to 2021. The house price index is constructed by following the repeat sales methodology from Case and Shiller (1987). To construct the property value, tax rate, and tax amount indices, I use a modified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

Figure 4: **Binscatter of square footage of purchased house by property tax rate, 2021**



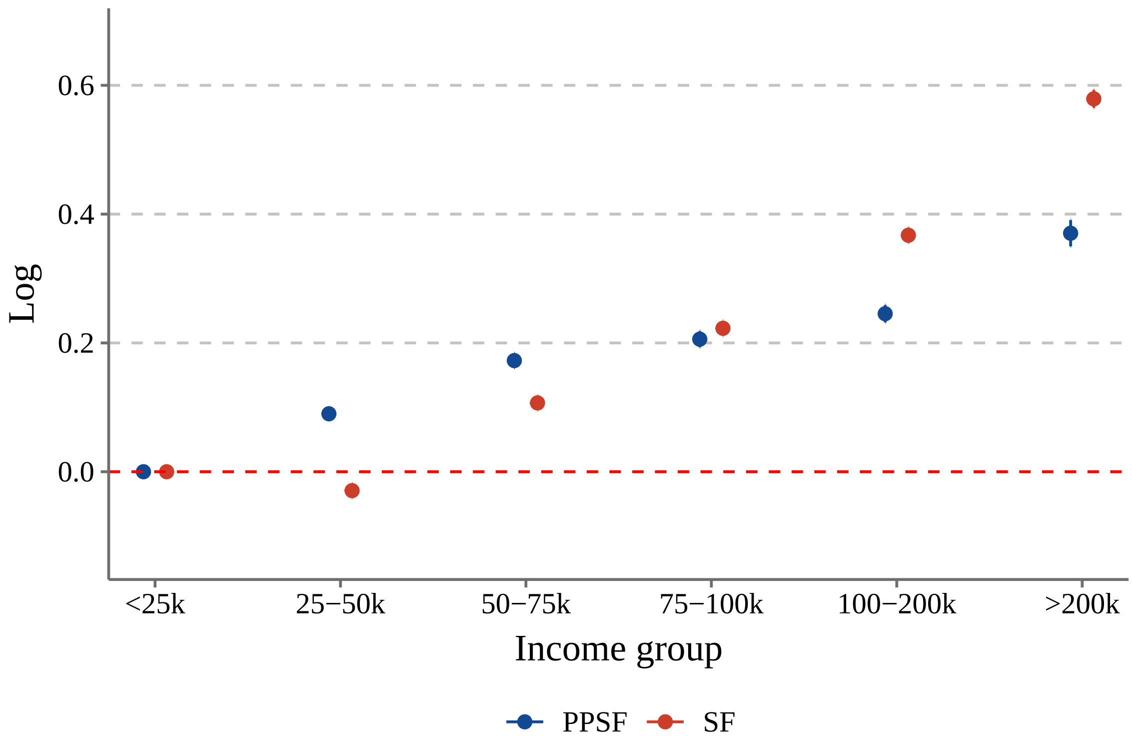
Note: This figure presents a residualized binscatter analysis of log square footage of purchased house by property tax rate using transactions in 2021. The binscatter analysis includes residualization for log household income. Results are additionally presented including and excluding residualization for housing prices, measured as log price per square feet.

Figure 5: **Nominal intrajurisdictional redistribution, 2021**



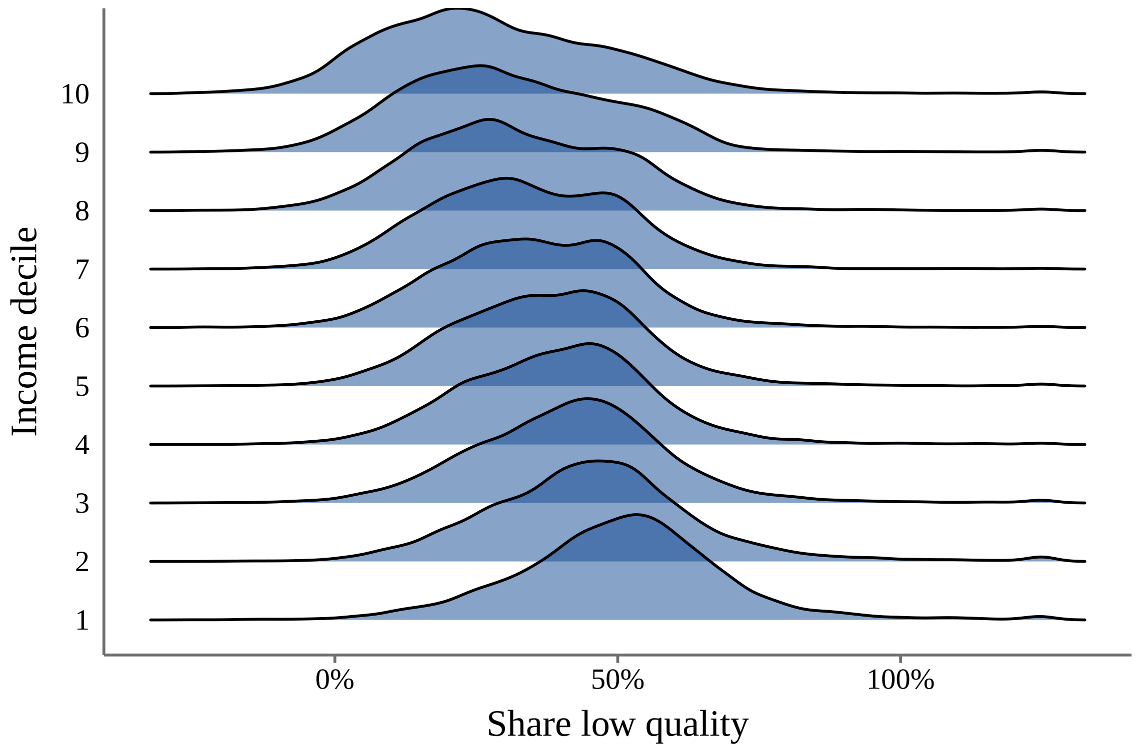
Note: This figure presents the estimated coefficients on household income percentile fixed effects for equation (1), where the outcome is property tax payment in 2021. Outcomes are ex-ante residualized by the average in the school district. Household income percentiles are defined using the national distribution of household income in the 2019 American Community Survey. Standard errors are clustered by school district.

Figure 6: **Residualized housing consumption by household income, 2021**



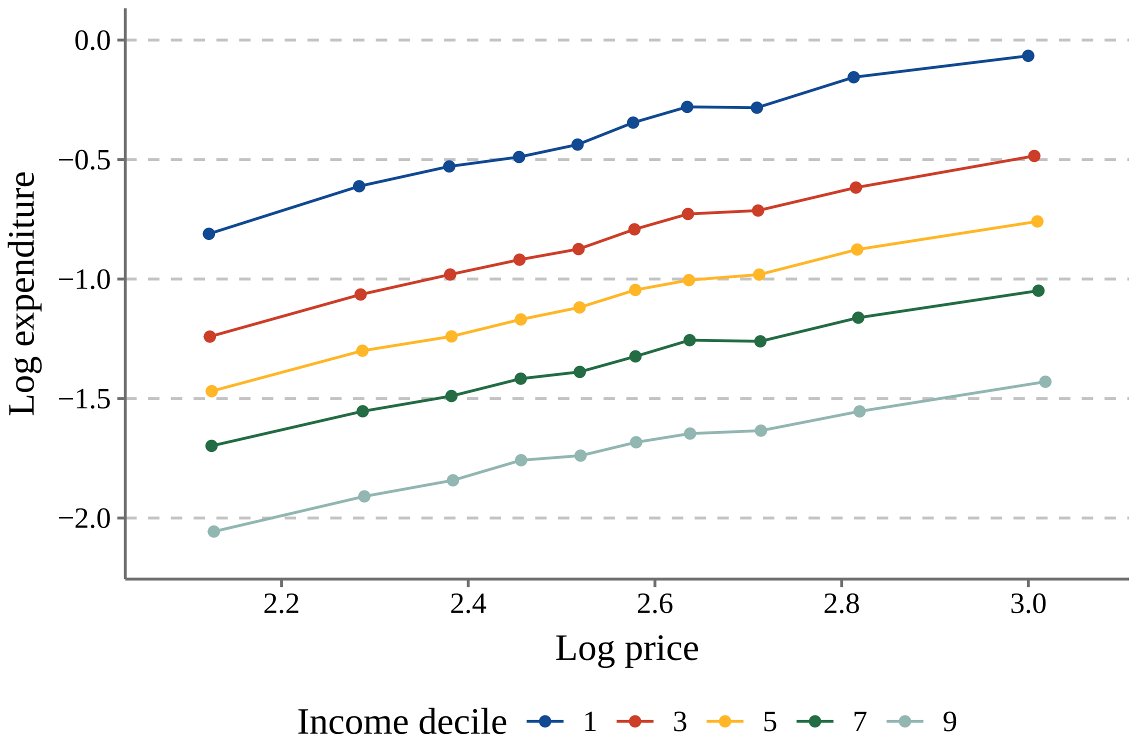
Note: This figure presents the estimated coefficients on household income group fixed effects for equation (2), where the outcomes are log house square footage and log price per square feet in 2021. Household income groups are defined as follows: (1) less than \$25,000; (2) \$25,000 to \$49,999; (3) \$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 7: **Distribution of taste parameter by income group, 2019**



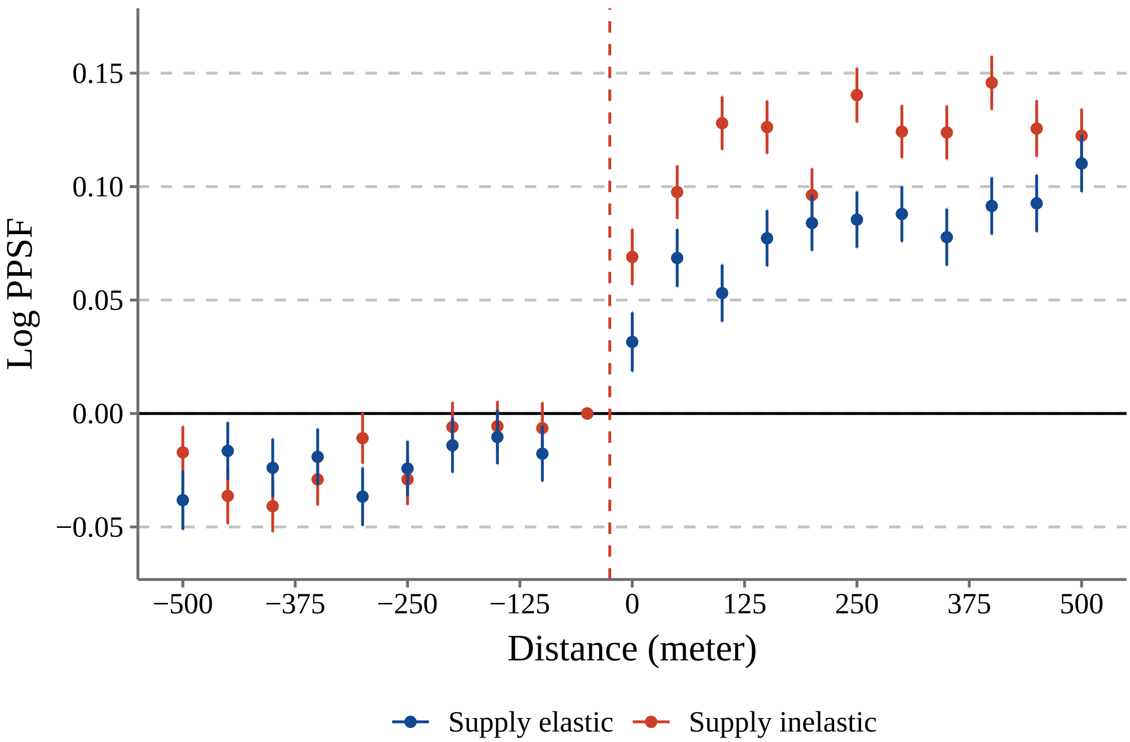
Note: This figure presents the distribution of the Cobb-Douglas parameter for the neighborhood-specific share of low-quality housing consumed by a household of a given income decile in 2019. A neighborhood is defined as a ZIP code.

Figure 8: **Binscatter of housing expenditure share by housing price, 2019**



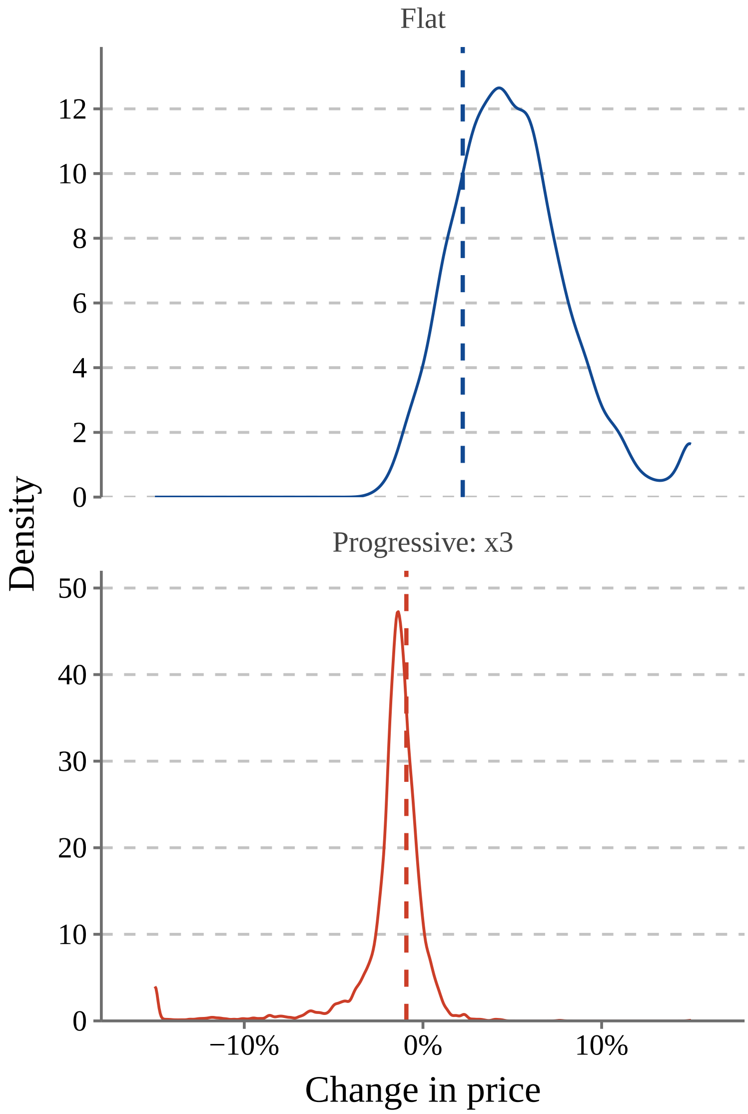
Note: This figure presents a cross-sectional binscatter analysis of log relative housing expenditure share and log housing prices by income deciles in 2019. Observations are at the ZIP code-income decile level.

Figure 9: **Border discontinuity with school district boundaries, 2009–2019**



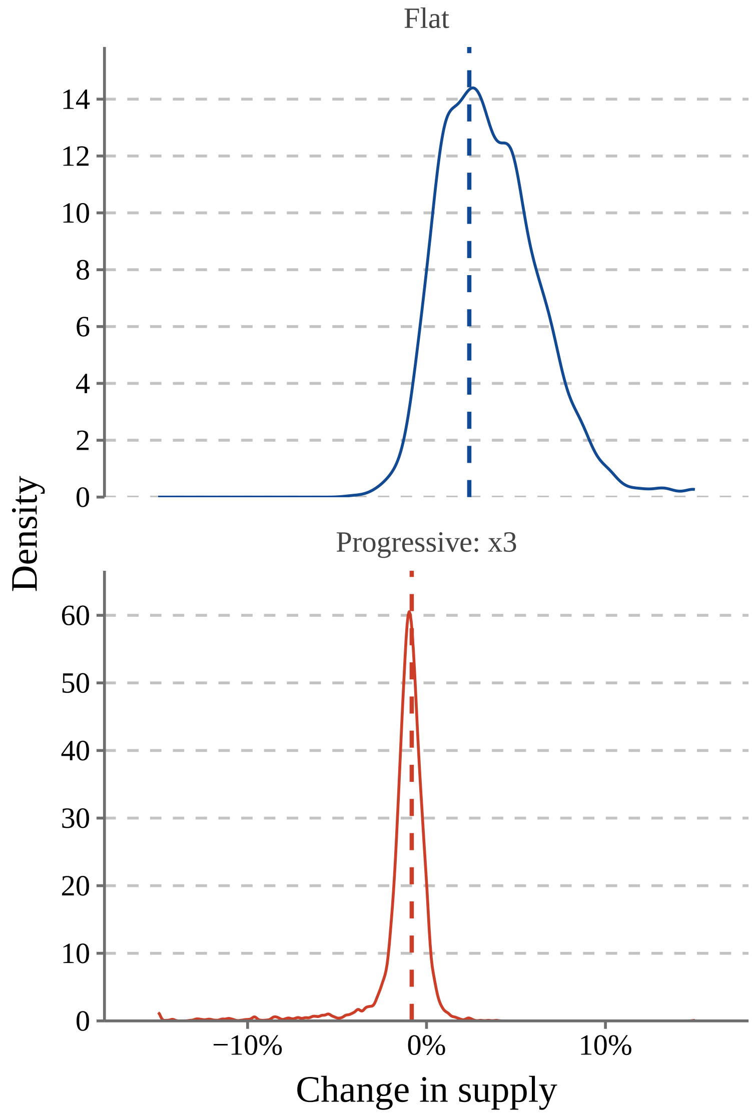
Note: This figure presents the coefficients from equation (8). Housing sales with a positive distance are located in school districts with higher test scores. Only school district boundaries located within the same municipality are included. Standard errors are clustered by school district boundary.

Figure 10: **Change in prices by school district, 2019**



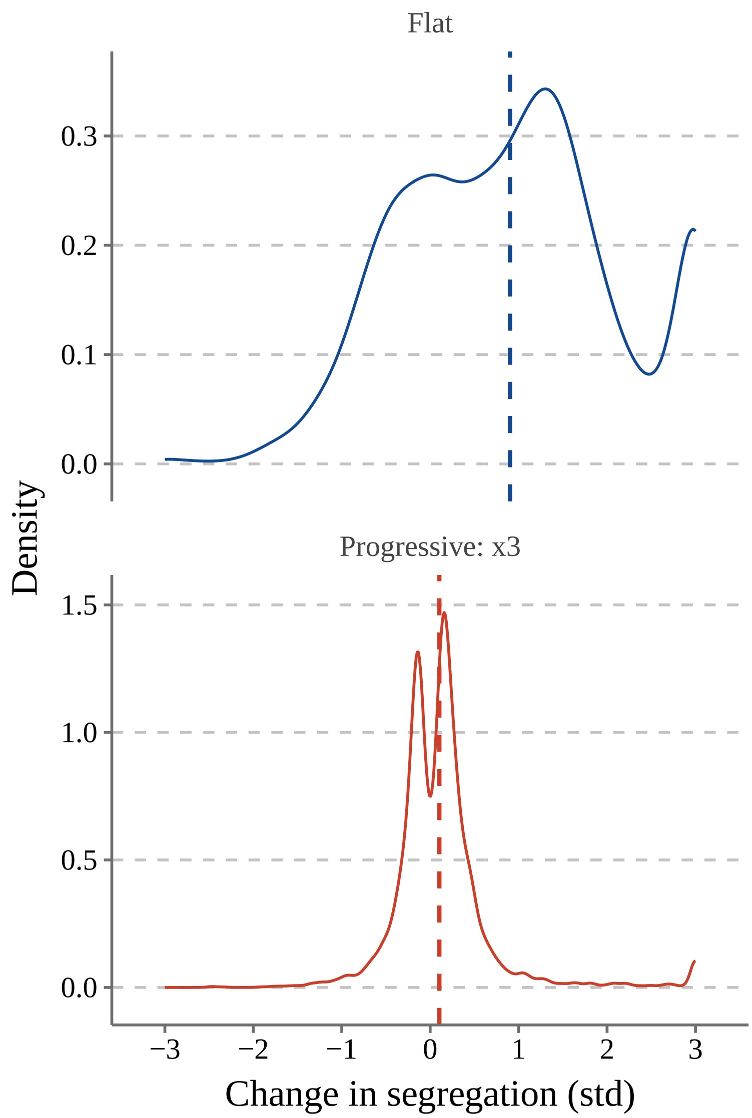
Note: This figure presents the distribution of changes in neighborhood-level average house prices switching from ad valorem property taxes to: (1) head taxes and (2) universal progressive property taxes where the marginal tax rate triples at the threshold.

Figure 11: **Change in square footage by school district, 2019**



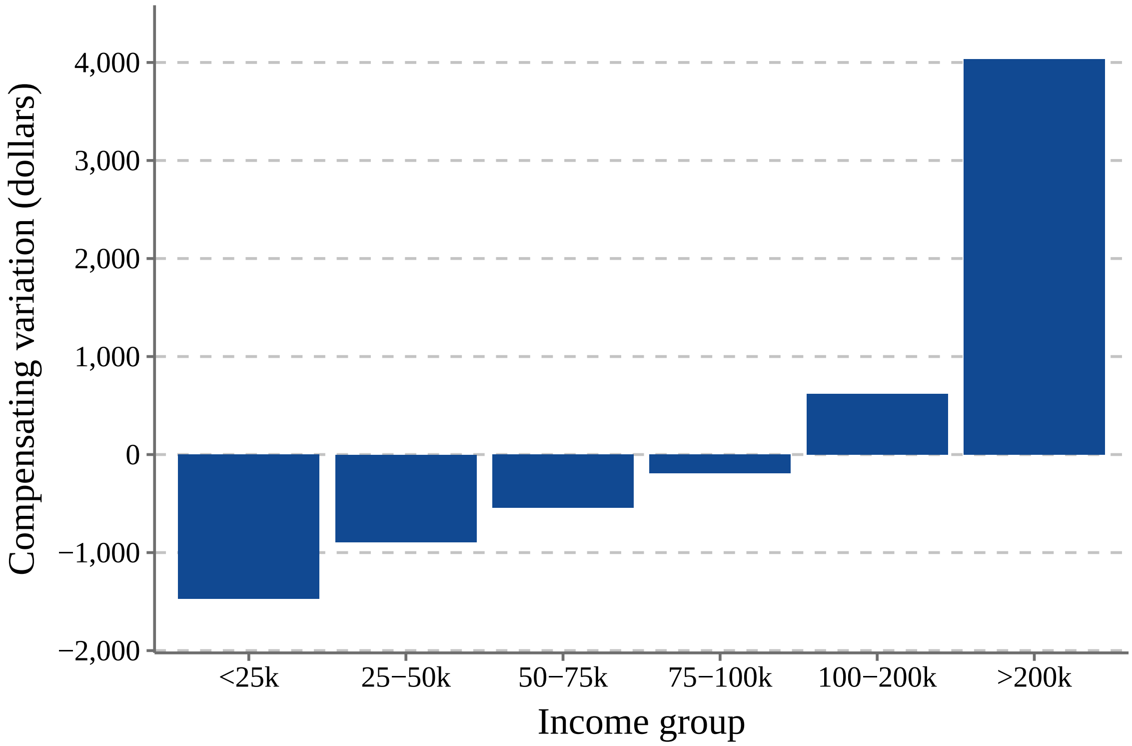
Note: This figure presents the distribution of changes in neighborhood-level total square footage switching from ad valorem property taxes to: (1) head taxes and (2) universal progressive property taxes where the marginal tax rate triples at the threshold.

Figure 12: **Change in income segregation by school district, 2019**



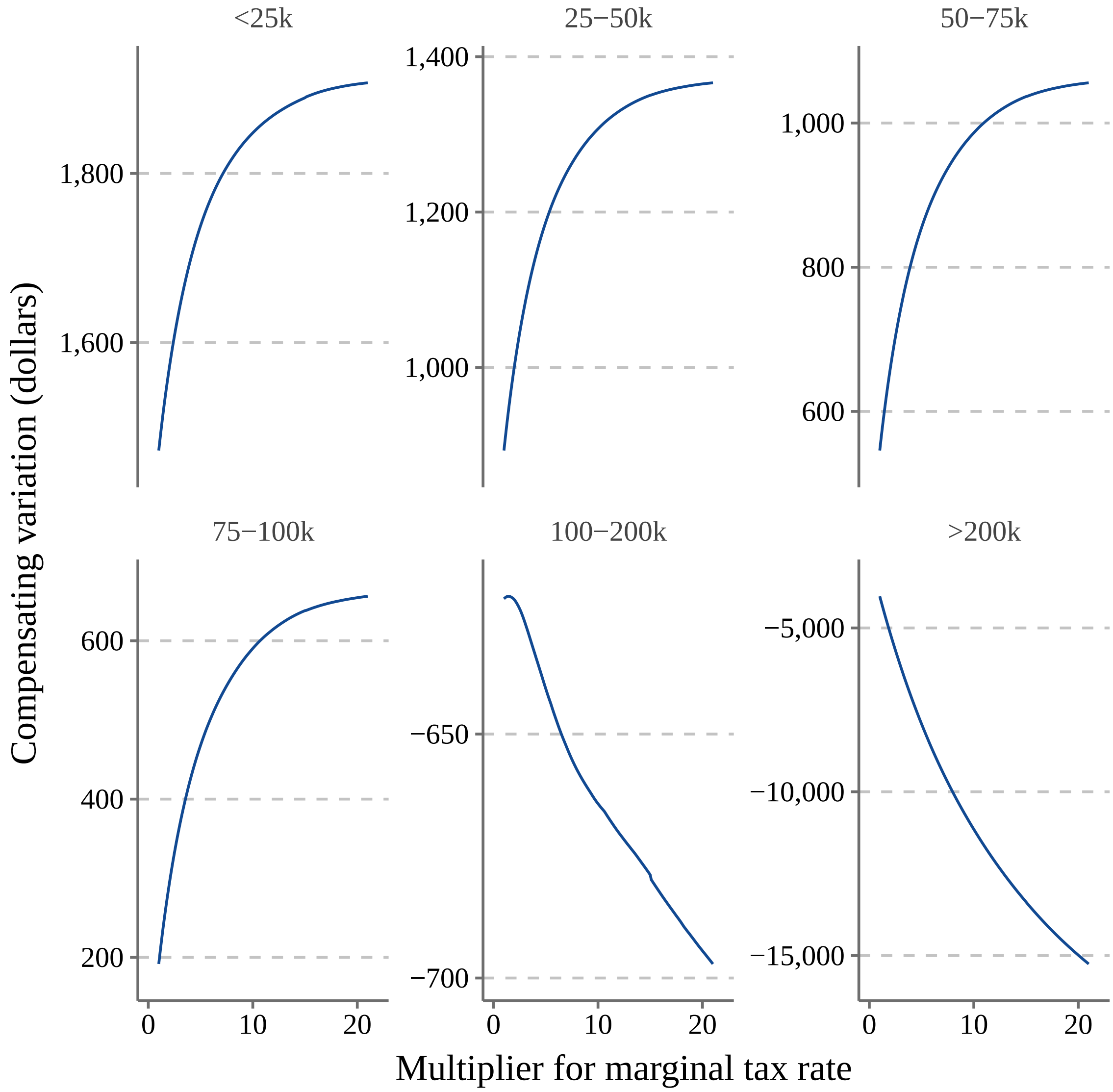
Note: This figure presents the distribution of changes in neighborhood-level income segregation switching from ad valorem property taxes to: (1) head taxes and (2) universal progressive property taxes where the marginal tax rate triples at the threshold. Income segregation is measured according to a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

Figure 13: **Welfare effect by income group: head tax, 2019**



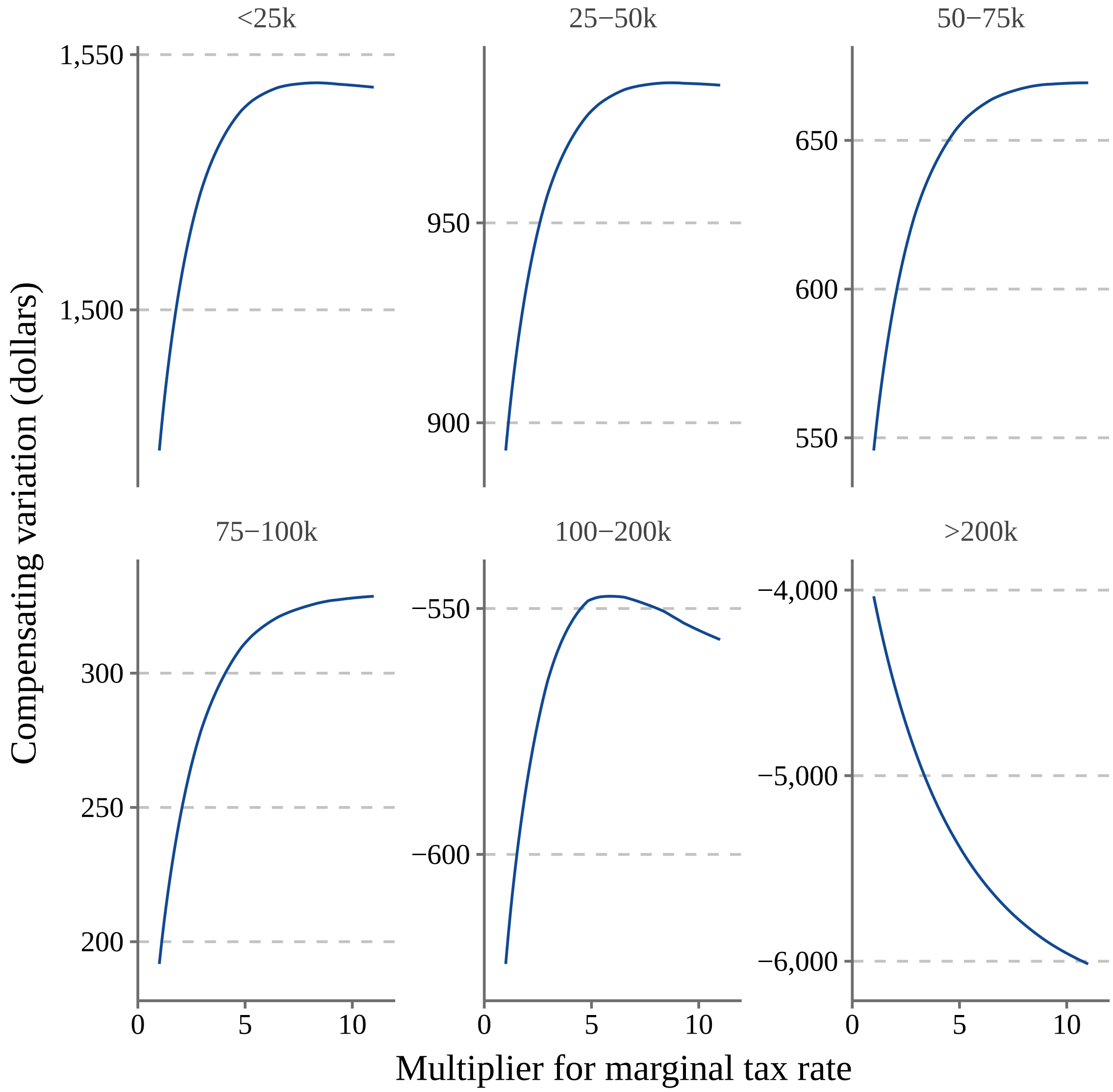
Note: This figure presents the welfare effects of switching from head taxes to ad valorem property taxes, where dollar amounts measure the compensating variation of the switch. Household income groups are defined as follows: (1) less than $25,000; (2) $25,000 to $49,999; (3) $50,000 to $74,999; (4) $75,000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

Figure 14: **Welfare effect by income group: centralized progressive tax, 2019**



Note: This figure presents the welfare effects of switching from head taxes to universal progressive 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 15: **Welfare effect by income group: decentralized progressive tax, 2019**



Note: This figure presents the welfare effects of switching from head taxes to progressive property taxes implemented only by the largest school district in each commuting zone, 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)**
$\log(r)$	0.575	0.742	0.562	0.728	0.538
	(0.015)	(0.109)	(0.015)	(0.104)	(0.078)
Bartik IV		1.324		1.553	1.553
		(0.189)		(0.198)	(0.198)
F-stat		464.1		610.3	610.3
Income FE	X	X	X	X	X
Commuting zone FE	X	X			
County FE			X	X	X
n	$34,905$	$34,905$	$34,905$	$34,905$	$34,905$

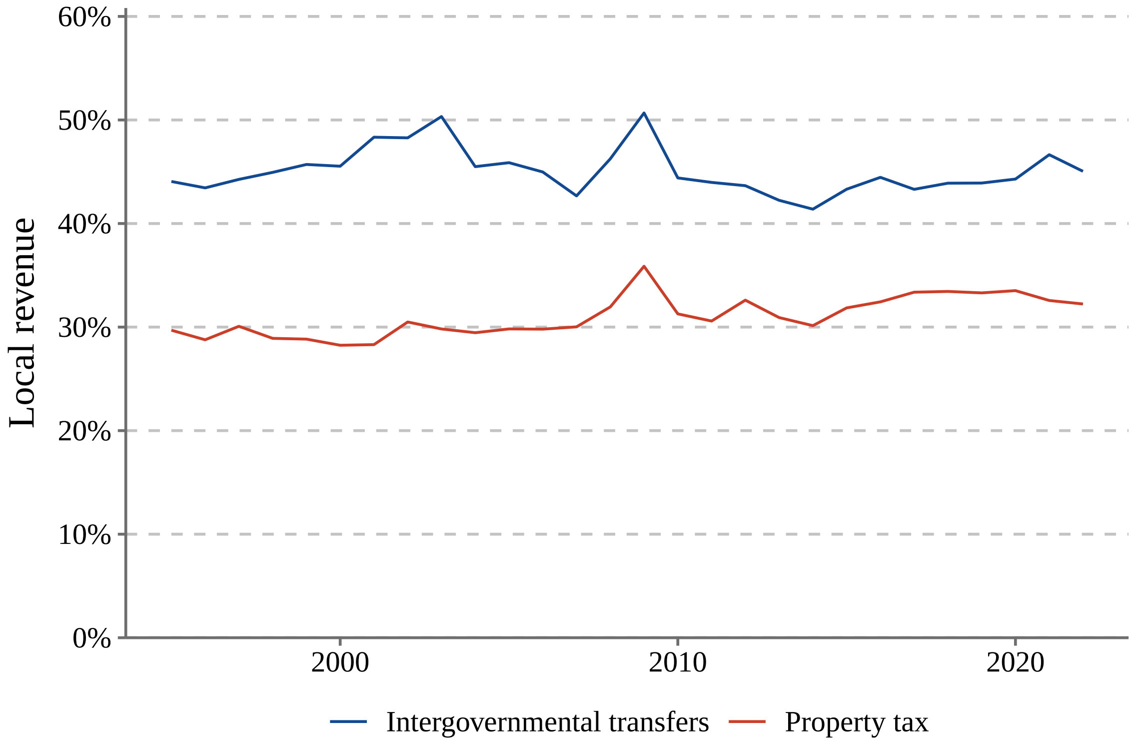
Table 2: **Migration elasticity: regression estimates**

	Coef.	Std. err.
$E[\beta]$	0.035	0.003
σ^{-1}	9.819	3.734
$n = 6,704,731$		

Apppendix

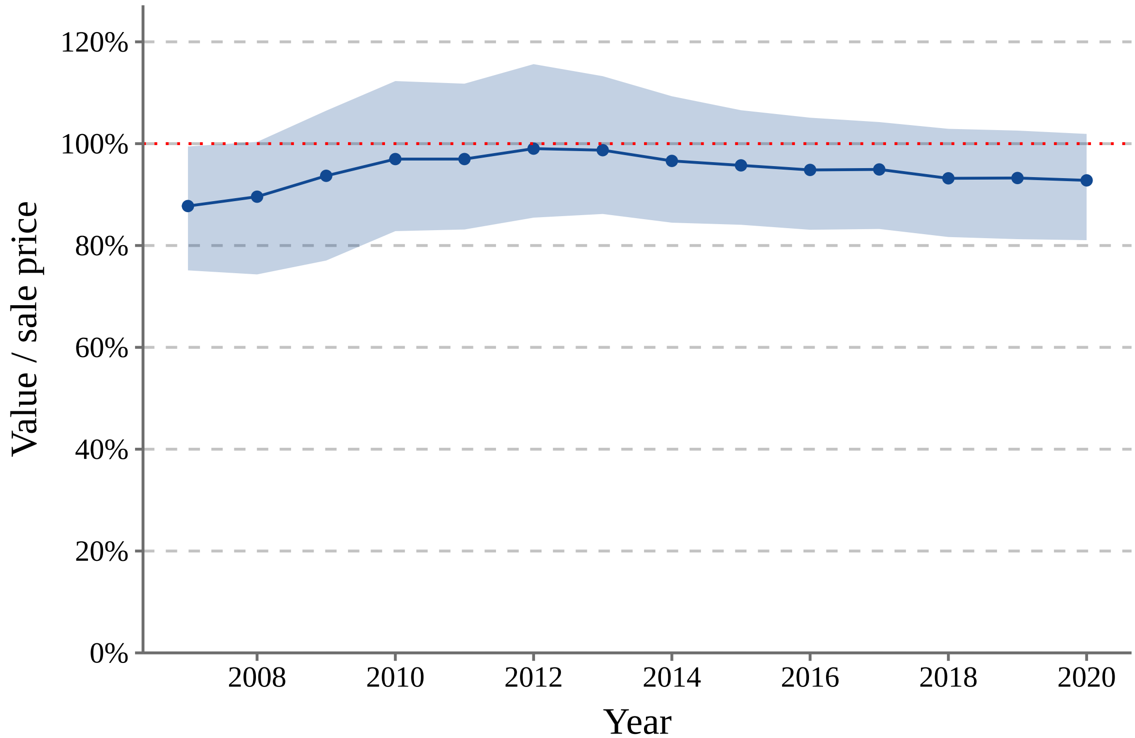
A Additional figures and tables

Figure A.1: **Sources of local government revenue, 1970–2022**



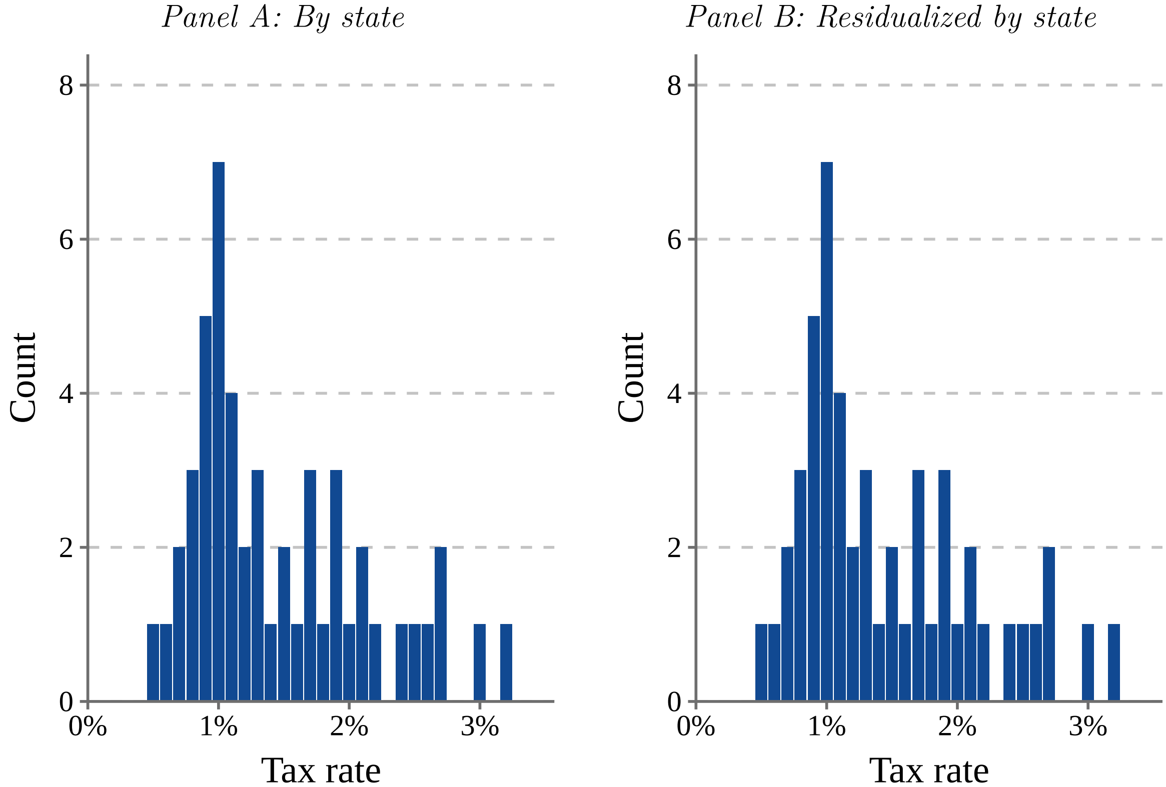
Note: This figure presents the share of local government revenue from different sources from 1970 to 2022 according to the Census of Governments. When measuring revenue, charges from public hospitals are excluded, as such charges are direct payments for medical services. Intergovernmental transfers refer to transfers from higher-level governments (e.g., the federal government).

Figure A.2: **Property value to sale price ratio, 2007–2020**



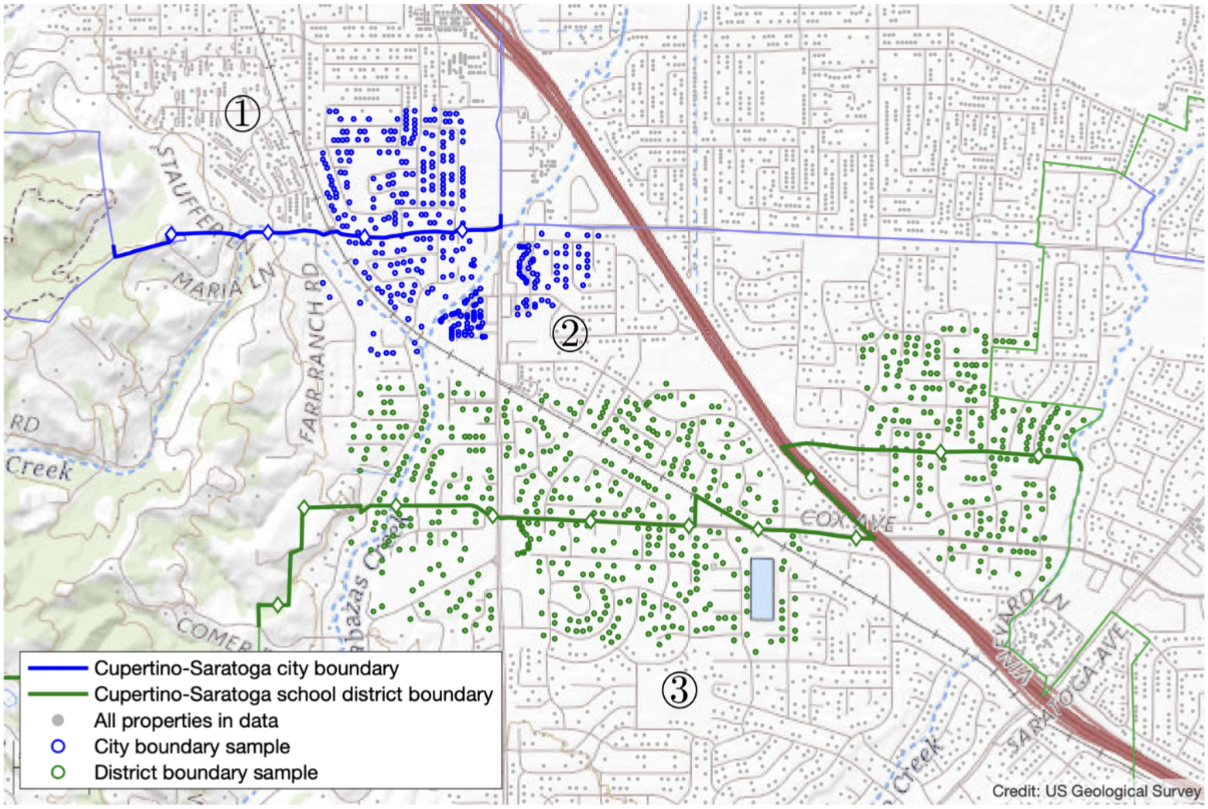
Note: This figure presents median property value to sale price ratio for transacted residential properties from 2007 to 2020. Ratios are calculated using property values from the current year and sale prices from the previous year, since property values are restrospective; e.g., ratios in 2007 are calculated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

Figure A.3: **Distribution of commercial property tax rates, 2021**



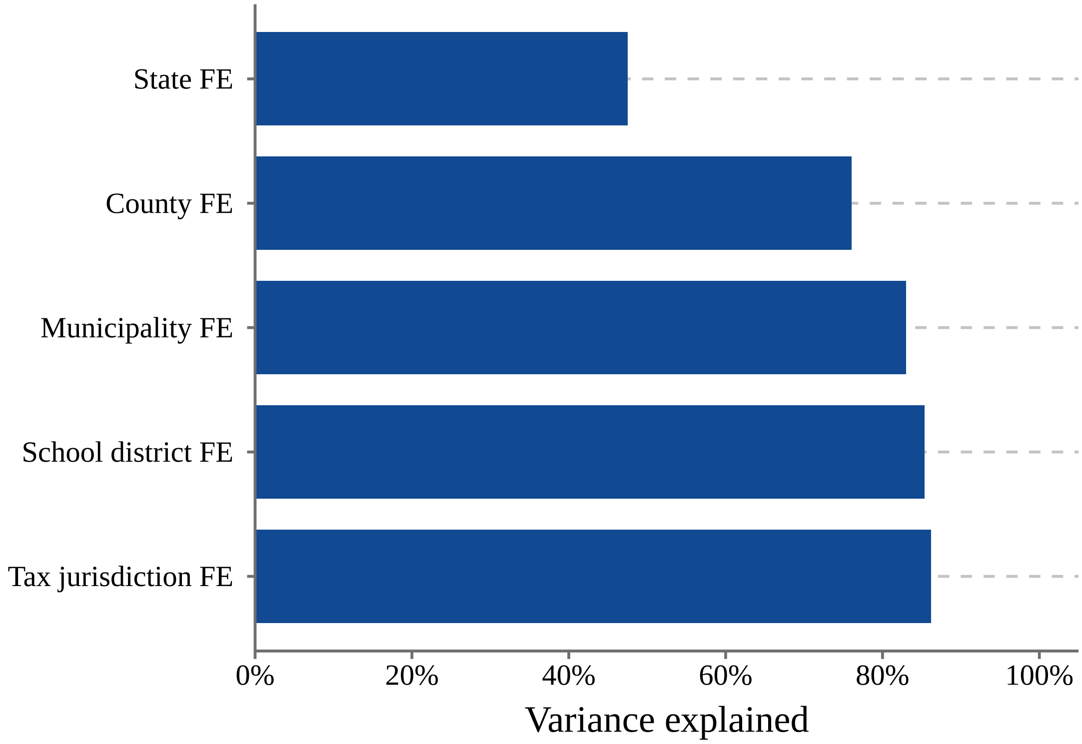
Note: Panel A of this figure presents the distribution of median commercial property tax rates in 2021 aggregated at the state level. Panel B of this figure presents the distribution of commercial property tax rates in 2021 after residualizing by state-specific median values.

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



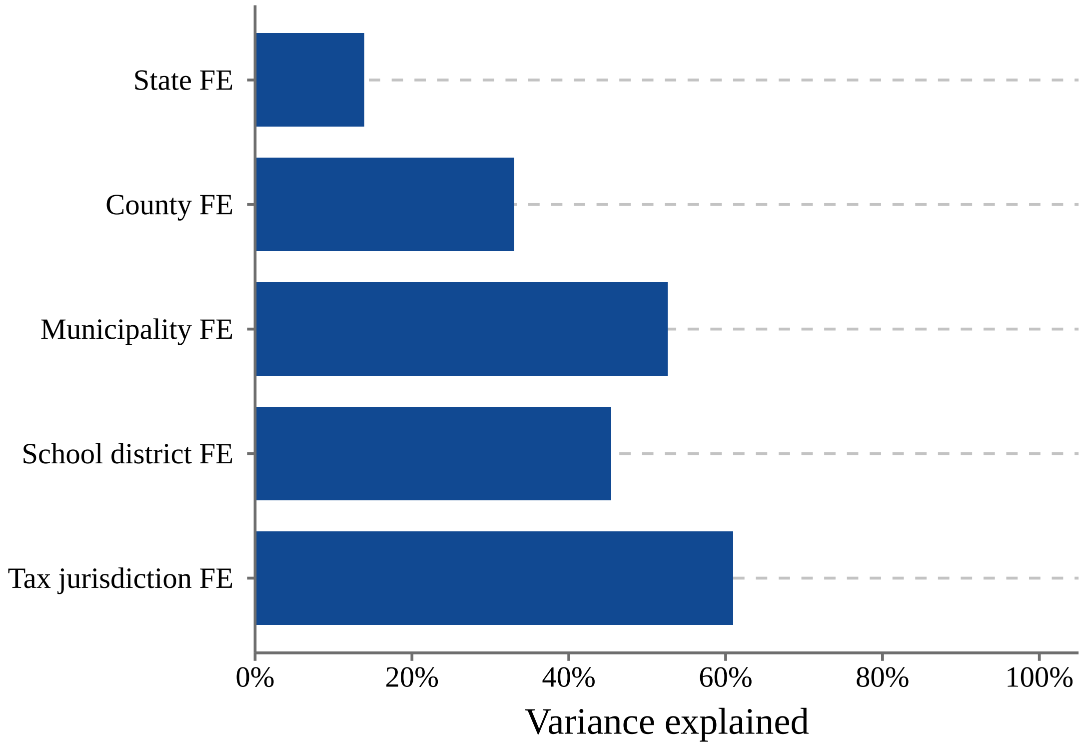
Note: This figure presents an example from Schonholzer (2024) of when municipality boundaries and school district boundaries are misaligned. Properties belong to one of three tax jurisdictions: (1) Santa Clara County/Cupertino City–Cupertino Union School District; (2) Santa Clara County–Saratoga City–Cupertino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

Figure A.5: **Variance decomposition of residential property tax rates, 2021**



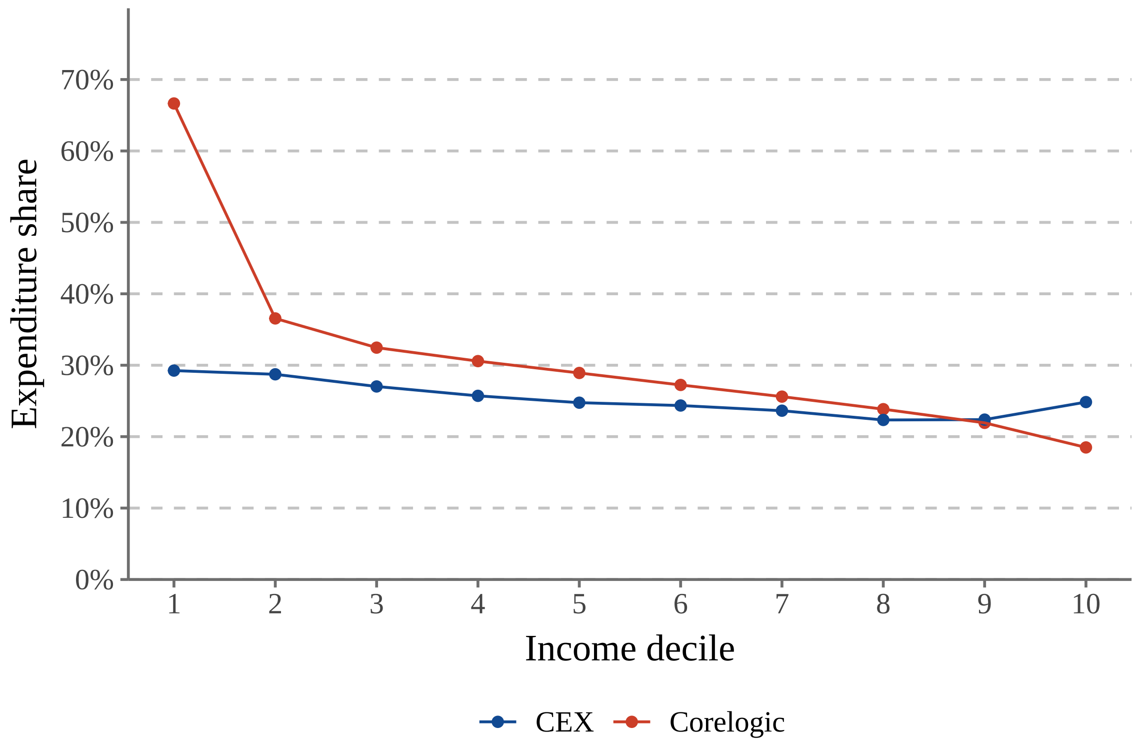
Note: This figure presents the proportion of variation in residential property tax rates explained by different levels of government in 2021. Tax jurisdiction refers to the specific combination of county, municipality, and special districts to which a parcel belongs.

Figure A.6: **Variance decomposition of commercial property tax rates, 2021**



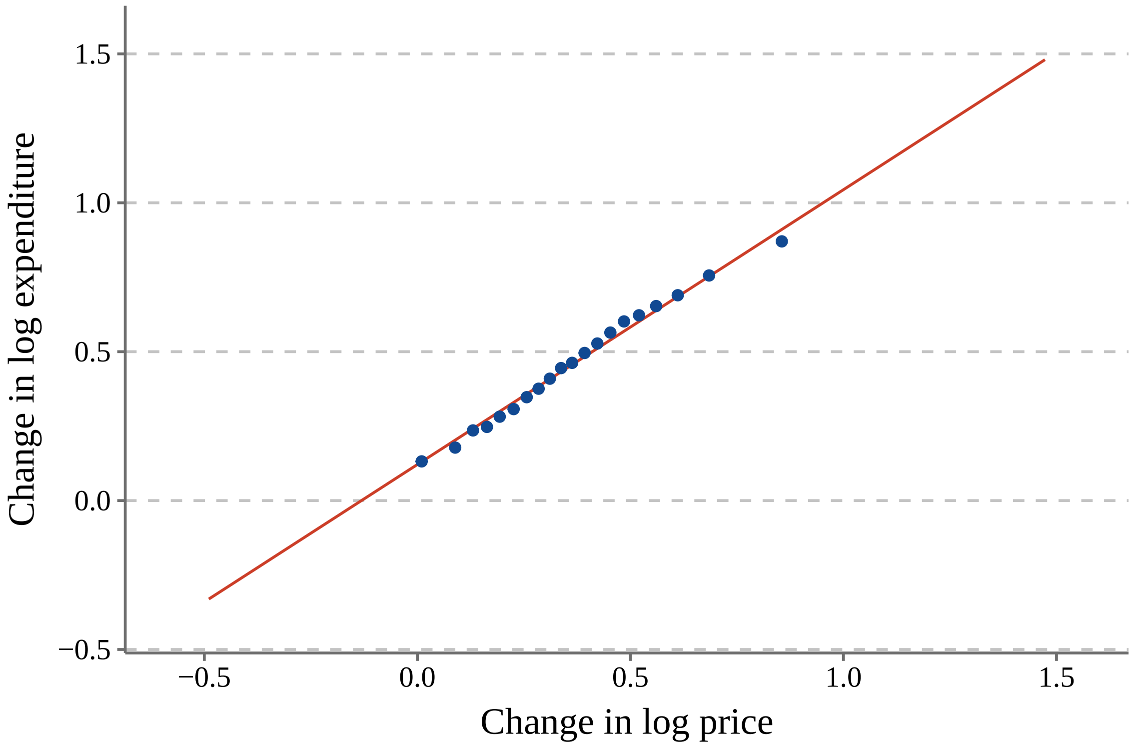
Note: This figure presents the proportion of variation in commercial property tax rates explained by different levels of government in 2021. Tax jurisdiction refers to the specific combination of county, municipality, and special districts to which a parcel belongs.

Figure A.7: **Housing expenditure shares by income group, 2019**



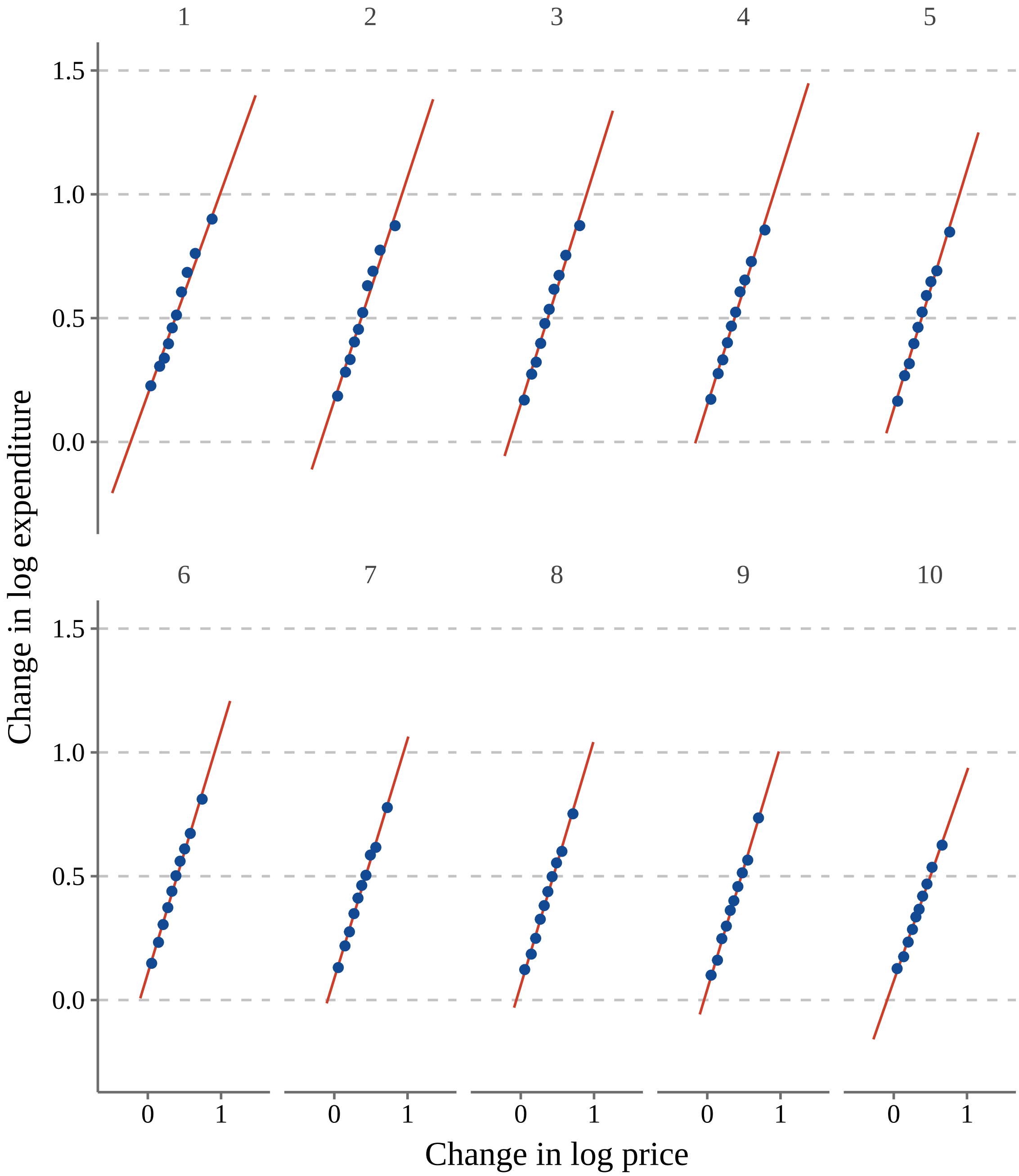
Note: This figure presents expenditure shares for housing by income group in 2019 across two samples: (1) the analysis sample; and (2) the 2019 Consumer Expenditure Survey (CEX). Expenditure shares calculated in the analysis use household income as a proxy for total household expenditure. In the CEX,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

Figure A.8: **Binscatter of changes in housing expenditure share by changes in housing prices, 2010–2019**



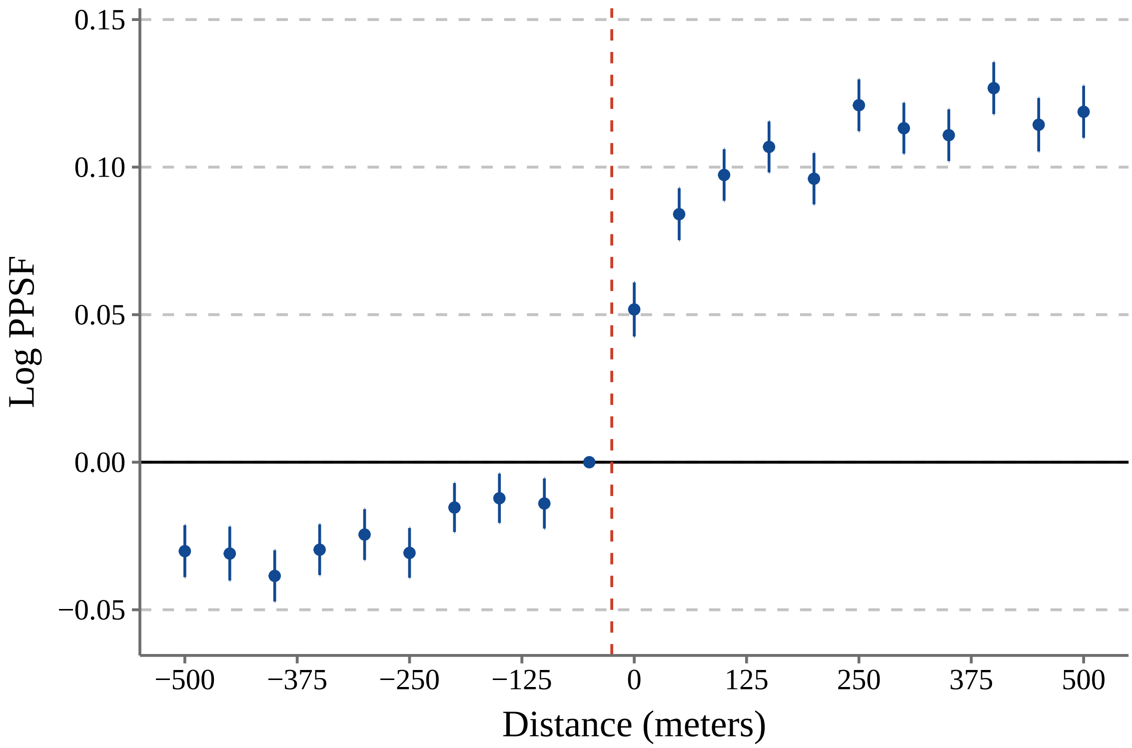
Note: This figure presents a binscatter analysis of changes in log relative housing expenditure share by changes in log housing prices from 2010 to 2019. Observations are at the ZIP code-income decile level.

Figure A.9: **Binscatter of changes in housing expenditure share and changes in housing price by income decile, 2010–2019**



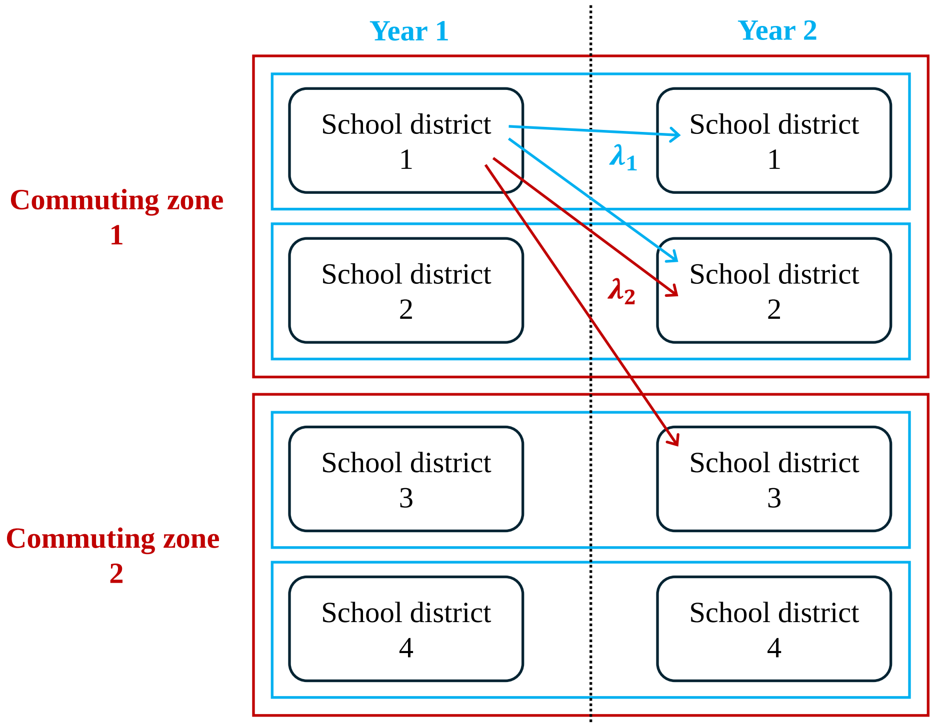
Note: This figure presents a binscatter analysis of changes in log housing expenditure share and changes in log housing price by income decile from 2010 to 2019. Observations are at the ZIP code-income decile level.

Figure A.10: **Border discontinuity with school district boundaries, 2009–2019**



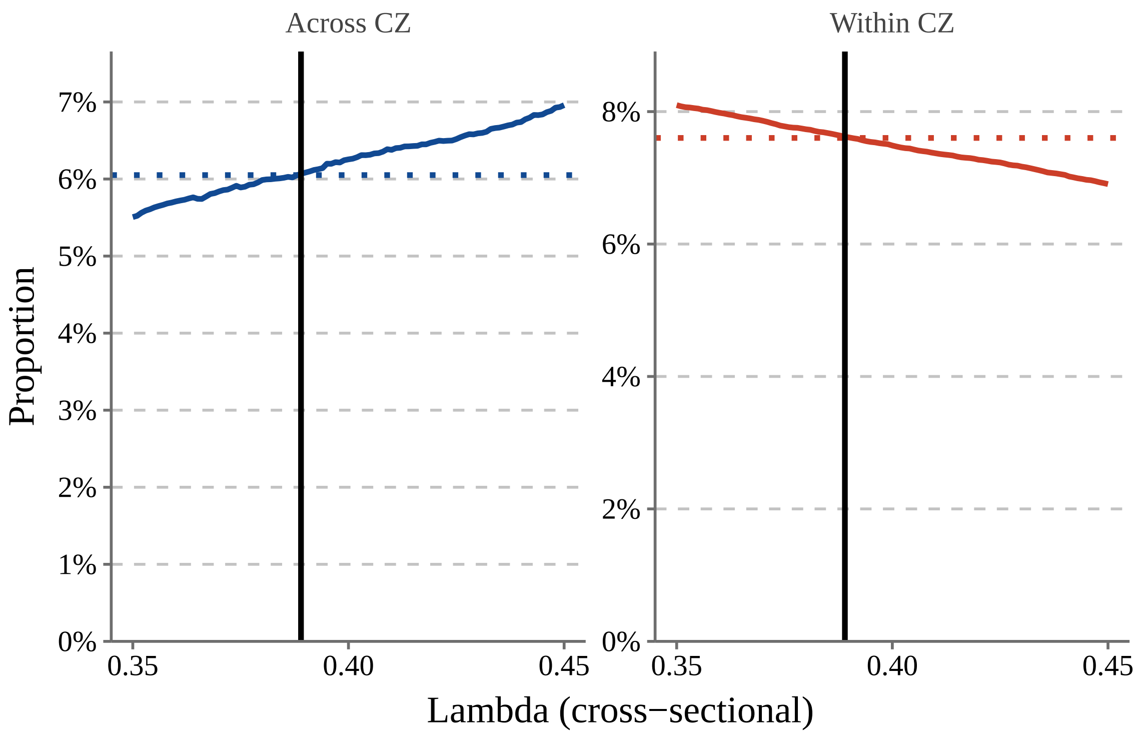
Note: This figure presents the coefficients from equation (8), excluding interaction terms for housing supply elasticity. Housing sales with a positive distance are located in school districts with higher test scores. Only school district boundaries within the same municipality are included. Standard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

Figure A.11: **Nesting structure for generalized extreme value distribution**



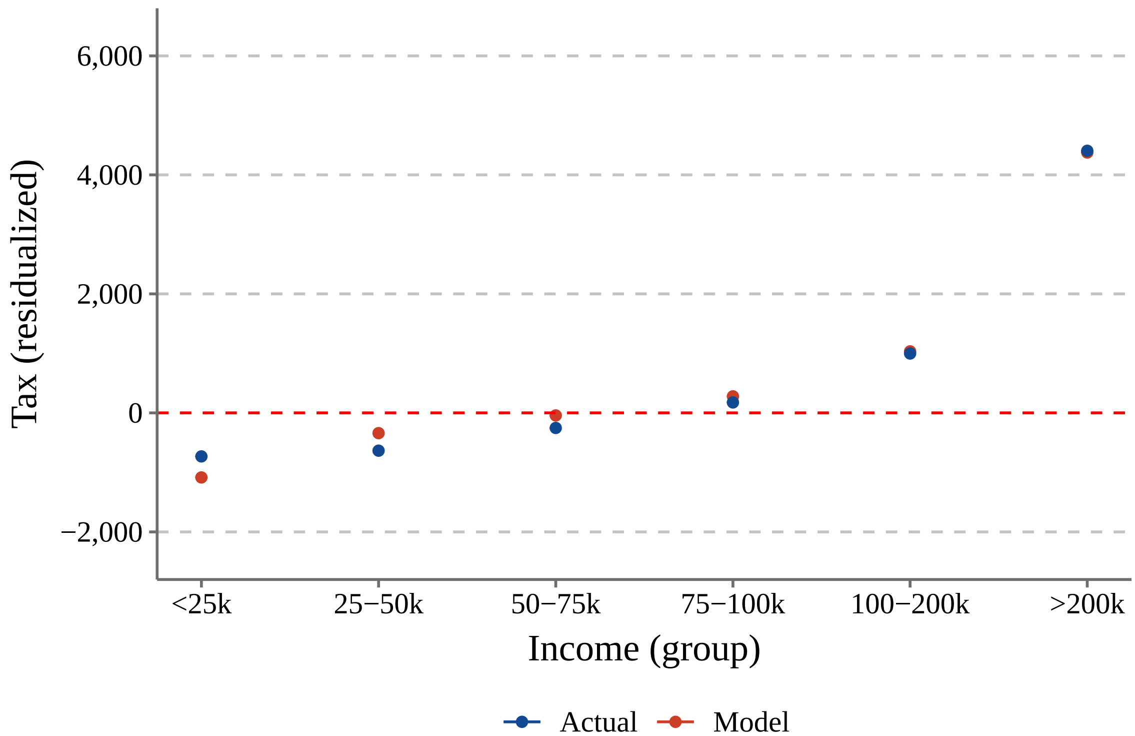
Note: This figure presents the nesting structure for the generalized extreme value distribution that characterizes household idiosyncratic preferences for school districts.

Figure A.12: **Simulated versus actual migration, 2019**



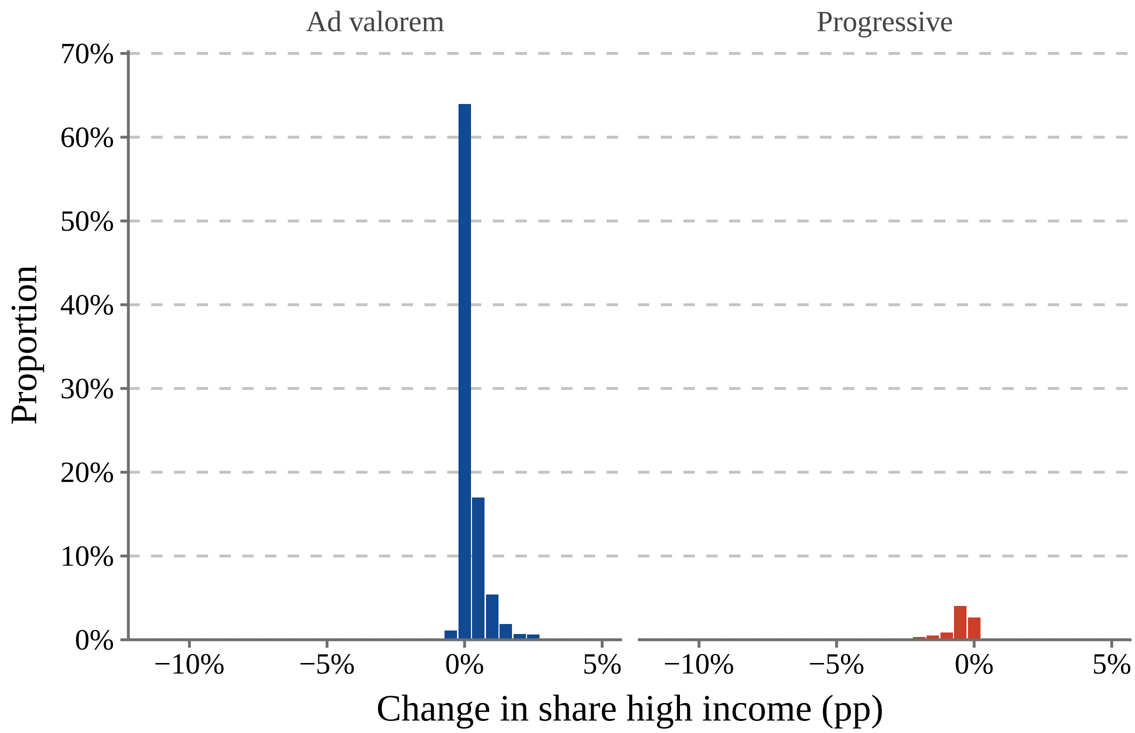
Note: This figure presents the moment equations used to identify the parameters of the generalized extreme value distribution. I fix the parameter $\lambda_1 = 0.16$ and present how gross migration shares change with the parameter λ_2. The dotted lines present the empirical moments for gross migration using 2019 data from Infutor.

Figure A.13: **Model-implied nominal intrajurisdictional redistribution, 2019**



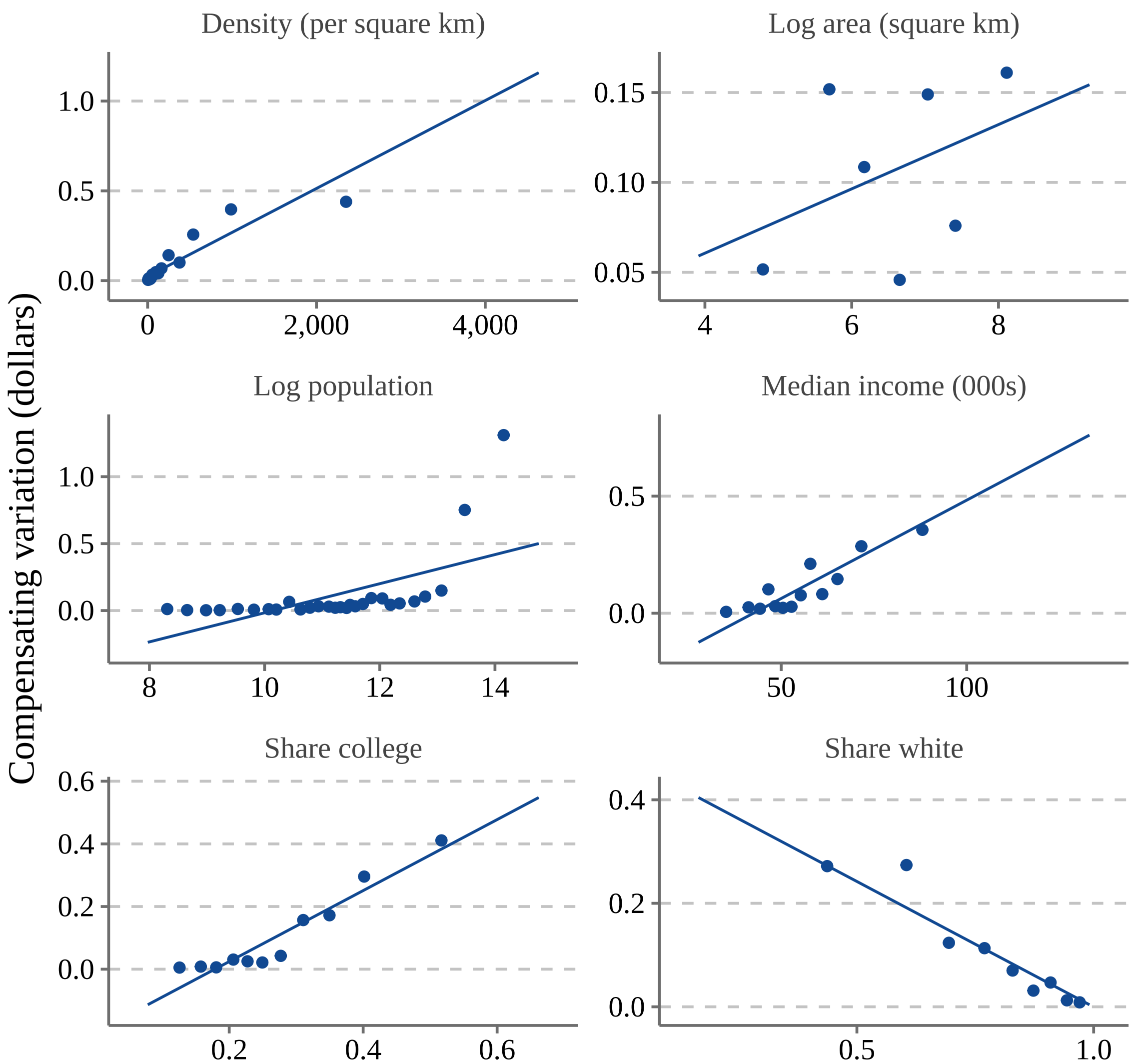
Note: This figure presents model-implied nominal intrajurisdictional redistribution by income group in 2019 using income-specific population shares from the Individual Income Tax Statistics. Model-implied nominal intrajurisdictional redistribution is benchmarked to nominal intrajurisdictional redistribution 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 A.14: **High-income household migration: decentralized progressive tax, 2019**



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

Figure A.15: **Welfare effects for low-income households: individual progressive tax, 2019**



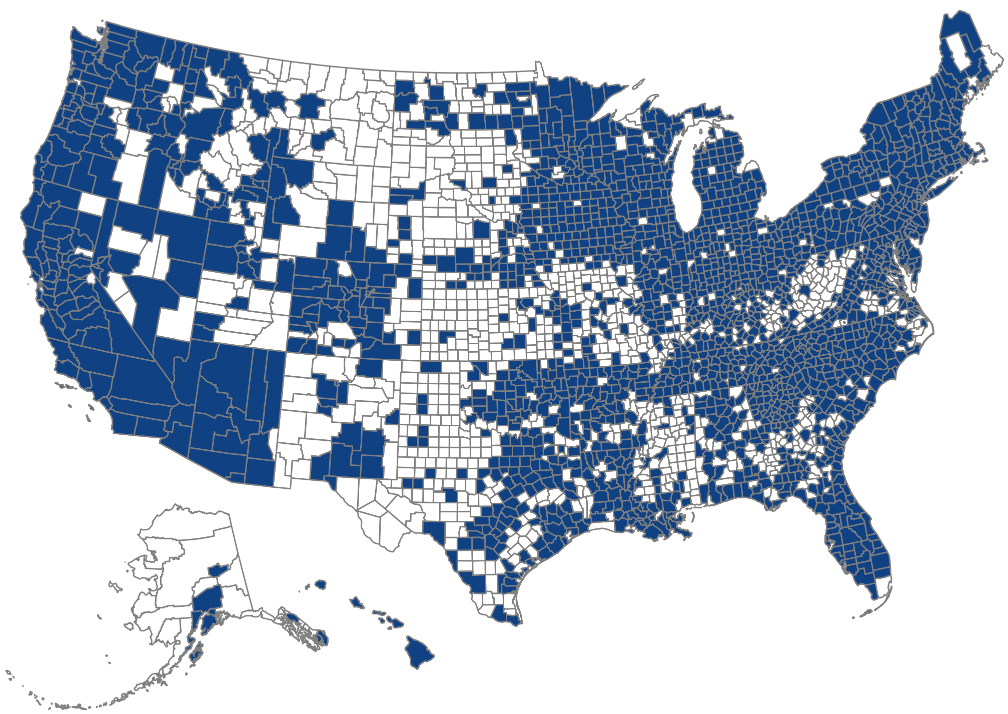
Note: This figure presents the welfare effects for low-income households (i.e., households than earn less than $25,000) when an individual school district implements progressive property taxes instead of ad valorem property taxes, where dollar amounts measure the compensating variation of the switch. Binscatter analyses correlate welfare effects of an individual school district implementing progressive property taxes to demographic characteristics of the school district.

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 B.1 provides a map of the counties in my sample, and Appendix Table B.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.[65]

Figure B.1: **Map of counties in analysis sample**



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

[65]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). While there exist other states with property tax limitations, limitations are significantly more permissive than California. 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 B.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
% white	3,220	82.5%	17.2%
% college	3,220	14.9%	6.5%
Analysis counties			
Population	2,070	148,659	396,001
Median income	2,070	$56,305	$14,583
% white	2,070	83.3%	14.6%
% college	2,070	16.3%	7.0%
Analysis counties, excluding CA			
Population	2,015	133,228	302,863
Median income	2,015	$55,972	$14,253
% white	2,015	83.6%	14.6%
% college	2,015	16.2%	7.0%

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.[66]

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 mortgage 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, and 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 after stop words. 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, year of mortgage application, and mortgage amount.

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

[66] Household income reflects pre-tax income amounts reported on mortgage applications. Mortgage lenders will typically verify an applicant's income by requesting documents such as paycheck stubs, tax returns, and bank statements. Mortgage lenders are incentivized to accurately assess income since mortgage payment-to-income ratios are an important predictor of loan default.

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 mortgages are not systematically different from matched mortgages. Appendix Figure C.1 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.

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.[67] 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%.

C.3 Validating household income

HMDA only provides household income for housing transactions associated with mortgage loans. Therefore, the CoreLogic–HMDA merge only allows me to observe income for homeowners, who typically have a higher income than renters. Appendix Figure C.2 presents the distribution of household income in the 2019 property tax assessments. 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.[68]

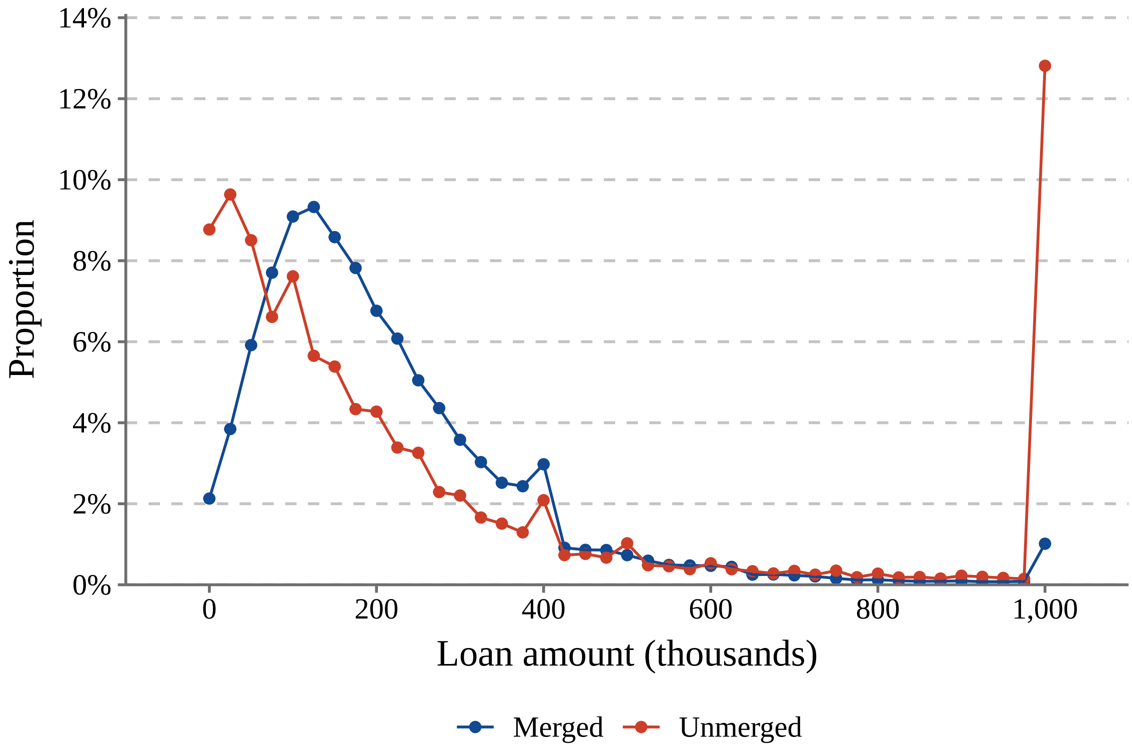
I find that the distribution of household income in my sample largely matches the distribution of household income for homeowners that recently purchased their house with a mortgage, suggesting that the income measures in the HMDA data are reasonably reliable.

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

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

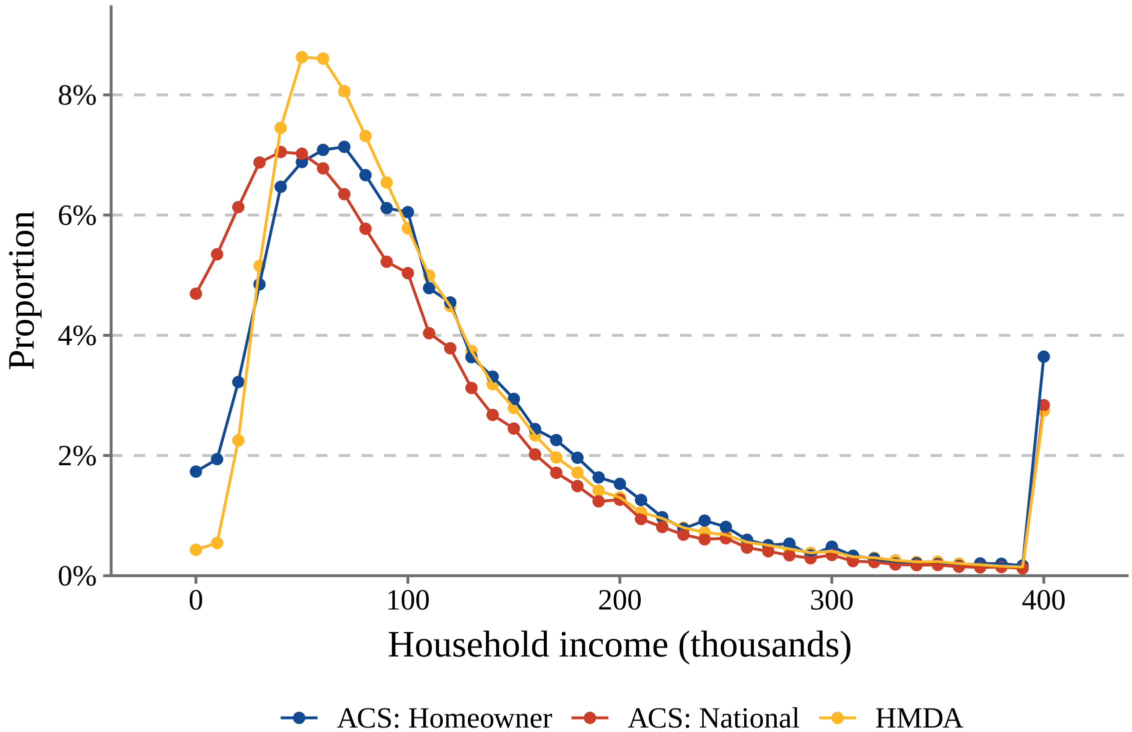
In contrast, household income in my sample is significantly skewed higher-income compared to the national distribution. To account for the fact that homeowners have a higher average income than renters, I reweight my sample to match the national distribution of income in the 2019 ACS. This reweighting ensures that my empirical analysis is representative of the national population.

Figure C.1: **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.

Figure C.2: **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.

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 Governments 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:

$$\log(p_{it}) = \lambda_{z_i t} + \gamma_{it} + \epsilon_{it}$$

where $\log(p_{it})$ is the log 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). The coefficients for $\lambda_{z_i t}$ can be interpreted as ZIP code-level price indices.

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 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.[69] The model with non-linear taxes differs from the model in Section 4 in set-up for the following subsection: (1) housing demand and (2) equilibrium.

E.1 Housing demand

Assume a unit measure of heterogeneous households, where households differ according to their type θ.[70] 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 $w_{\theta j}$ and 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:

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

[69] 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.

[70] For empirical implementation, household types are defined by household income. Descriptive evidence suggests that household income is a sufficient statistic for housing demand. For example, controlling for household income, there is no economically significant relationship between household size and housing demand. Appendix F provides more detail.

where:

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

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 housing consumption. The parameters $\alpha_\theta \alpha_j$ govern the neighborhood-specific *appeal* of housing relative to non-housing consumption for type θ households.[71] Heterogeneity in the taste and appeal parameters across type allow households to implictly have non-homothetic preferences for housing consumption. Heterogeneity in the taste and appeal parameters across neighborhoods capture unobserved differences in housing variety between neighborhoods.

Each household's optimal housing consumption is characterized by one of the following, depending on whether it is optimal for the household to consume before the threshold, at the threshold, or after the threshold:

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

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. Quality-specific optimal housing consumption is given by:

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

Households choose to live in the neighborhood that maximizes their utility.

[71] I assume log-additive separability by type in the neighborhood-specific appeal of housing; i.e., $\log(\alpha_{\theta j}) = \log(\alpha_\theta) + \log(\alpha_j)$. I directly test and fail to reject this assumption in the data. For example, Figure 8 provides descriptive evidence validating the assumption.

E.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 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.[72] 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.[73]

Local prices (r_{jL}, r_{jH}) and taxes $(T_j, \tau_{1j}, \tau_{2j}, k_j)$ 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:

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

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

[72] Since I define household type as income and local government revenue is primarily used to fund K-12 education, this assumption is equivalent to assuming that there is no within-neighborhood correlation between household income and number of children attending public school. Among households where the head is a working-age adult, number of children attending public school is relatively constant by household income. Appendix F explores an extension of the model where the marginal cost of providing amentities to households is heterogeneous by household type.

[73] 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.

F Household heterogeneity

F.1 Household type

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:

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

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 F.1 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 0.2%. Controlling for household income, there is no economically significant relationship between household size and housing demand. Holding household income fixed, households with an additional person consume 1.5% more housing. Results are qualitatively similar using other measures of housing consumption, such as annual property tax payment or monthly rent payment (F.2).

F.2 Heterogeneous household fiscal costs

In my model in Section 4, I assume that the fiscal cost of an additional household is homogenous by household type, which I define as household income. To assess whether this is a reasonable assumption, 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 F.1). Number of children attending K-12 public school is a good proxy for the fiscal cost of an additional household since revenue raised from property taxes is largely used to fund elementary and secondary education. 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. Appendix Table F.3 presents the results of the following regression equation:

$$y_i = \alpha + \beta \log(w_i) + Elderly_i + \epsilon_i$$

where y_i is the number of children attending K-12 public schools for household i, w_i is annual household income, and *Elderly* is an indicator for whether the head of household is age 65 or older. Controlling for whether the head of household is elderly greatly attenuates the relationship between the average number of children attending K-12 public school per household and household income.

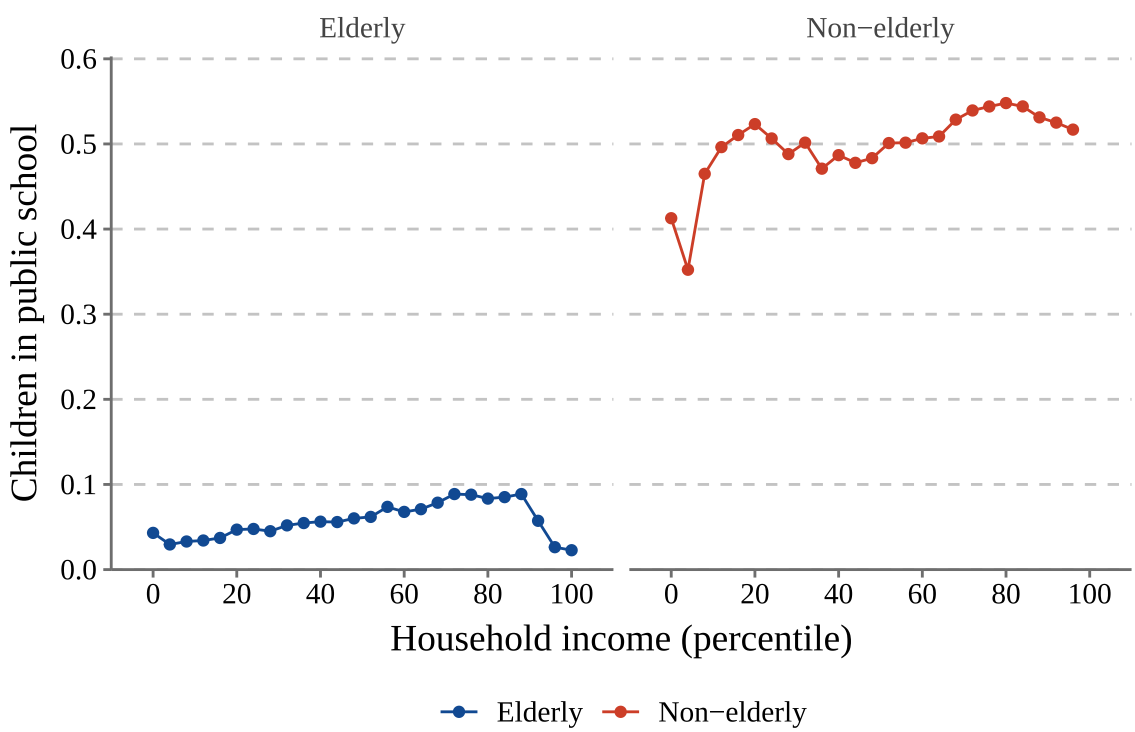
Table F.1: **Determinants of housing consumption in 2019, owner occupied**

	Market value			**Property tax**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\log(w_i)$	0.464	0.4601	0.460	0.464	0.458	0.460
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Household size		0.009	0.015		0.015	0.010
		(0.001)	(0.001)		(0.001)	(0.001)
Other covariates			X		X	X
R^2	0.191	0.191	0.193	0.152	0.152	0.153
n	562,158	562,158	562,158	562,158	562,158	562,158

Table F.2: **Determinants of housing consumption in 2019, renter occupied**

	Rent		
	(1)	**(2)**	**(3)**
$\log(w_i)$	0.281	0.270	0.264
	(0.001)	(0.001)	(0.001)
Household size		0.041	0.044
		(0.001)	(0.001)
Other covariates		X	X
R^2	0.255	0.267	0.272
n	255,148	255,148	255,148

Figure F.1: **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.

Table F.3: **Determinants of number of children attending K-12 public school, 2019**

	(1)	**(2)**
$\log(w_i)$	0.060	0.023
	(0.001)	(0.001)
$Elderly_i$		-0.440
		(0.002)
R^2	0.006	0.065
n	1,262,479	1,262,479

G Labor demand shocks and housing quality

For equation (5) in Section 5.1, I instrument for changes in rent prices with ZIP-code level Bartik labor demand shocks $Bartik_j$.[74] I make the identification assumption that local labor demand shocks are uncorrelated with changes in neighborhood-specific appeal of housing $\Delta \log(\alpha_j)$. 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.

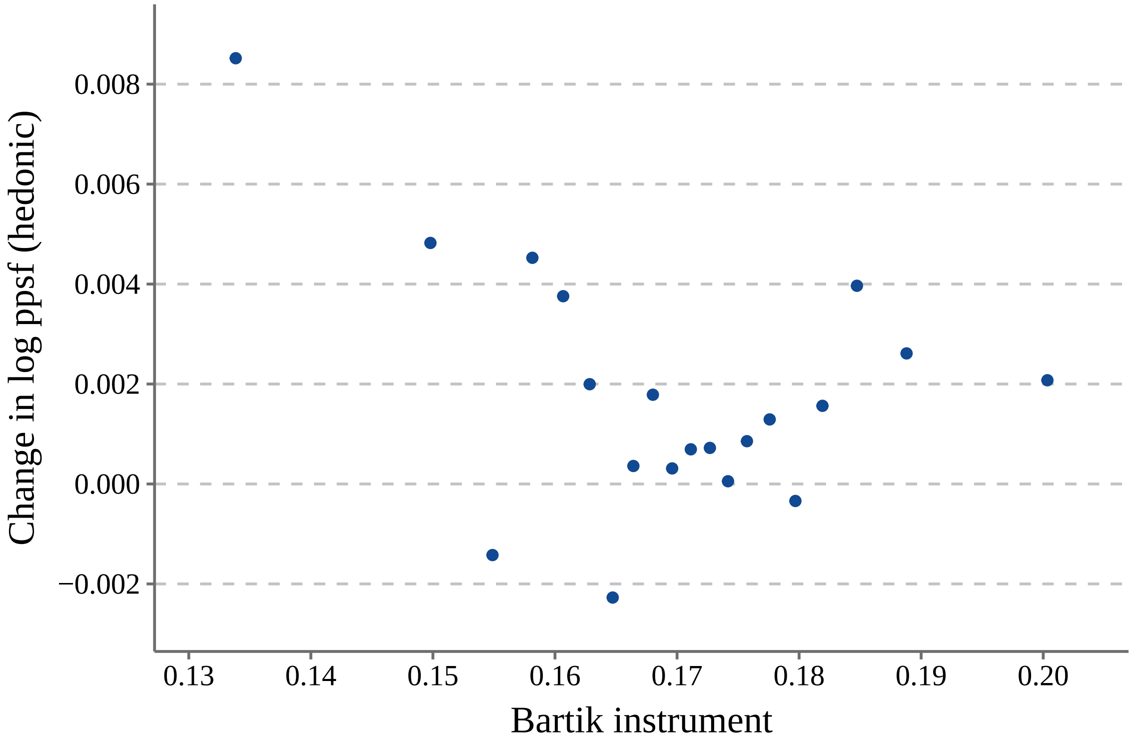
One concern is that local labor demand shocks improve the quality of housing relative to non-housing through new construction and renovations, making housing more appealing relative to non-housing consumption. To test this, I first run the following hedonic regression using housing transactions from 2010:

$$\log(p_i) = \delta X_i + \epsilon_i$$

where $\log(p_i)$ is log price per square feet for sale i and δX_i are covariates (i.e., quadratic terms for house age, building size, number of bedrooms, number of bathrooms, and lot size). I then use the hedonic regression to predict log price per square feet for transactions in 2010 and 2019 and construct ZIP code-level indices of housing appeal by averaging the predicted log prices per square feet. Figure G.1 presents a binscatter analysis correlating ZIP code-level changes in housing appeal with Bartik labor demand shocks from 2010 to 2019. I find minimal changes in the composition of the type of housing sold in 2010 relative to 2019, rejecting the concern that local labor demand shocks are correlated with changes in housing appeal.

[74] 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.

Figure G.1: **Binscatter of changes in predicted hosing price by Bartik labor demand shock, 2010–2019**



Note: This figure presents a binscatter analysis of changes in predicted log price per square feet by Bartik labor demand shock from 2010 to 2019. Observations are at the ZIP code level.