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Essays in Urban Economics

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ESSAYS IN URBAN ECONOMICS

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Chapter 1 examines how land use regulation affects residential segregation by income. Residential segregation by income severely limits access to opportunity for low-income households, restricting prospects of upward mobility. Land use regulations are one potential determinant of such segregation. However, establishing a causal link between such regulation and segregation faces two econometric challenges. First, regulation is potentially endogenous. Second, proper measurement of segregation is difficult. Concerning the first challenge, the prior literature relies on instrumental variables that may not be valid. Concerning the second challenge, the prior literature relies on measures that ignore the spatial dimension of segregation. This paper uses a new instrumental variable strategy and measures of segregation that account for the spatial distribution of neighborhoods within US metropolitan areas. The key findings are that stricter overall land use regulation *decreases* segregation within metropolitan areas and that accounting for the spatial aspect of segregation matters. However, the negative effect appears to be driven by state involvement and approval delay; other types of regulation, such as residential density restrictions and local zoning approval complexity, may *increase* segregation.

Chapter 2 examines how property tax assessment caps affect new home building permits and housing stock growth using county-level panel data from the US Census Bureau and longitudinal state-level tax policy data from the Lincoln Institute of Land Policy. Property tax assessment growth limits ensure smaller, more predictable changes in taxable value of property, reducing the share of property taxes on rapidly appreciating property. This helps cash-poor homeowners keep appreciating homes if tax rates don't rise. However, these limits distort decisions on whether to move, whether to invest in property, and where to locate by conditioning reassessment on changes in property ownership, use, size, or zoning. This paper constructs a county-level panel dataset for a fixed effects regression analysis to estimate how homestead property tax assessment caps affect new homebuilding. The findings are inconclusive. Results using a levels regression are consistent with homestead assessment caps increasing homebuilding by reducing the expected future tax costs of owner-occupied housing assets. When the dependent variable is the inverse hyperbolic sine of the number of new housing units issued building permits, results are consistent with assessment caps decreasing homebuilding by increasing the tax cost of property changes.

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This is dedicated to my parents and grandparents who have encouraged and inspired me.

CHAPTER 1

How land use regulation affects residential segregation by income

1.1 Introduction

Residential segregation by income varies widely across metropolitan areas (MSAs) in the United States and has been rising since the 1970s with a brief pause in the 1990s (Reardon et al. 2018). The percent of families living in neighborhoods with median income outside 50-150% of the MSA median rose from 15% in 1970 to 34% in 2012 (Galster and Sharkey 2017). Residential segregation is higher and has risen most among households with children (Chetty et al. 2014, Owens 2016, Reardon et al. 2018). Residential income segregation deprives these families not only of higher quality local amenities like good schools and safe streets but also of diverse social networks that share specialized expertise and career assistance. Rothwell and Massey (2015) estimate the lifetime earnings gap between a top- and bottom-quartile census tract is $910,000. Hence, segregation impedes social and economic mobility and increases social and economic inequality (Chetty et al. 2014, Chetty and Hendren 2018, Ewing et al. 2016, Fogli and Guerreri 2019, Jargowsky 2018, Owens et al. 2016, Reardon and Bischoff 2011, Rothwell and Massey 2015).[1]

[1] The United States exhibits wide geographic disparities both between and within metro areas in upward social and economic mobility (Intrator et al. 2016, Galster and Sharkey 2017, Lens 2017). Housing costs reduce intergenerational economic mobility by making it harder for low-income households to live in high-opportunity

Land use regulation may contribute to residential segregation. Residential land use regulations can protect a community's public amenities but slow housing stock growth and raise housing costs, contributing to income sorting between and possibly within MSAs (Glaeser and Gyourko 2018, Ganong and Shoag 2017). Restricting the quantity of housing within a high-demand area limits residential access to those most willing to pay. Metro-wide residential zoning restrictions raise fixed costs of housing, circumscribing lower-income housing options. Higher income households outbid lower income households for limited housing within highly regulated high-opportunity MSAs. This may concentrate high-income households in high-demand neighborhoods and sort lower-income households into lower opportunity or more peripheral neighborhoods within those MSAs as well as into separate MSAs entirely.

Local land use rules may affect housing markets and the income distribution of residents not only within their own jurisdictions but also in other jurisdictions across the broader economic region. Local zoning laws across the United States restrict residential density to varying degrees. Without density restrictions, rising residential land values in high-demand neighborhoods encourage higher density development until the premium per housing unit disappears. Density limits preserve housing unit premiums in high-demand neighborhoods, geographically separating the housing market by income level.

While density restrictions are expected to increase residential segregation, it is not obvious that land use regulation should always increase residential segregation. If residential preferences favor sorting by income, then (especially if neighborhood quality changes over time) higher costs of obtaining project approval may reduce residential re-sorting (Schelling 1971). Thus, MSAs

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neighborhoods and still finance education and save (Chetty et al. 2020). Residential income segregation creates unequal opportunities that deprive poorer children regardless of their potential (Jargowsky and Wheeler 2017, Acs et al. 2017).

with stricter land use regulations may have lower residential segregation. Ultimately, the size and direction of any effect of land use rules depends on the nature of residential preferences.

The Schelling (1971) model presents full residential segregation as the unique stable equilibrium under even a slight preference for living amonst peers. Building off Schelling's checkerboard model of segregation, imagine a checkerboard with rich and poor people buying a location on a checkerboard without any restrictions on the number of people per square and no preferences over squares or neighbors. Rich and poor people will randomly disperse across the board. Without locational preferences, restricting density would not substantively affect segregation because it would only increase the average distance between everyone on the checkerboard. However, with locational preferences, density restrictions can affect segregation. By increasing the price of squares in high demand locations, density restrictions increase income segregation. Nevertheless, permitting restrictions that raise the fixed cost of moving would slow any re-sorting. Thus, in general, land use regulations have an ambiguous effect on income segregation.

This paper investigates how land use regulation influences residential segregation by income in MSAs, using a segregation measure that accounts for the spatial distance between neighborhoods. I hypothesize that density restrictions will increase spatial segregation and high-income residential concentration by making housing in high-demand areas highly supply inelastic. Other land use restrictions may raise or lower segregation.

Examining segregation between neighborhoods within MSAs requires a definition of neighborhood boundaries. A neighborhood alludes to a local spatial area of regular physical social interaction, but no uniform definition of boundaries exists. Segregation measures commonly use census tracts or block groups to proxy neighborhood boundaries. Chetty et al.

(2014) observes sharp contrasts in economic mobility even at the block level in some MSAs, suggesting segregation may matter at many spatial scales.

Traditional segregation measures compare characteristics across neighborhoods within an MSA without accounting for distance between neighborhoods. Effective segregation may be less severe when high- and low-income neighborhoods are close together than when they are distant. Ranking MSAs by residential segregation depends on the choice of measure and level of analysis: Census block, block group, tract, etc. (Lee et al. 2008). This paper's primary segregration measure, the spatial information theory index from Reardon and O'Sullivan (2004), accounts for varying degrees of spatial proximity between neighborhoods.

Spatial scales matter for segregation. Aspatial measures don't capture proximity between sub-areas, resulting in the checkerboard problem (Lens 2017, Reardon and O’Sullivan 2004). The problem is that a metro area with segregated neighborhoods dispersed evenly throughout the metro area (like red and black squares on a checkerboard) would score no differently than a metro area with equally segregated neighborhoods concentrated (like a board all red on the left and all black on the right). But these two different situations seemingly convey very different notions of segregation. Thus, it is important for metro area residential segregation measures to reflect the spatial distribution of people within the metro area.

Aspatial measures also suffer from the modifiable areal unit problem: sensitivity to the choice of sub-area unit land area size and boundaries to the extent proportions of population groups in nearby sub-areas vary. Tract and block group land area shrinks with population density (Lee et al. 2019). While residents of less dense areas in car-oriented suburbs may regularly cover greater geographic distance, residents in denser areas may regularly interact with a larger population. Tract-based aspatial measures may thus overstate segregation in densely populated areas and understate it in less dense areas.

The spatial information theory index better reflects the lack of distinct neighborhood boundaries in densely populated areas.[2] Spatial weights capture the proximity of nearby areas beyond sub-area unit boundaries (Reardon et al. 2006; Reardon et al. 2008; Lee et al. 2008; Reardon and Bischoff 2011; Lee et al. 2019). Adopting the spatial information theory index from Reardon and O'Sullivan (2004) allows this paper to account for the proximity of people in one block group to people in nearby block groups and explore how land use regulation might affect spatial evenness at different geographic scales.

The analysis here closely relates to two prior empirical studies, Rothwell and Massey (2010) and Lens and Monkonnen (2016), that indicate density-restricting land use regulation increases segregation. Rothwell and Massey (2010) find density zoning restrictions increase residential income segregation in US MSAs but find no evidence of an effect for other land use regulations or broader indices like the 2005 Wharton Residential Land Use Regulation Index (WRLURI). They measure segregation via a Neighborhood Gini coefficient, an exposure index of poor to affluent, and a poverty dissimilarity index.[3] Rothwell and Massey measure maximum permitted dwelling units per acre and other zoning rules using Pendall, Puentes, and Martin (2006)'s 2003 survey of local land use regulations in 1,677 out of roughly 5,000 total jurisdictions in the 50 largest MSAs in the United States. Rothwell and Massey's two-stage least squares (2SLS)

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[2] See Reardon et al. (2008) and Population Research Institute (www.pop.psu.edu/mss) on spatial measures.

[3] See the Appendix section below or Rothwell and Massey (2010) for a description of these segregation measures.

estimates use year of statehood and MSA population density in 1910 as IVs and control for socioeconomic and environmental characteristics.

Lens and Monkkonen (2016) find lot size minimums increase segregation of the high and middle income but not low income. Municipal review process complexity and local political pressure to restrict land use also increase segregation. State involvement in land use regulation reduces income segregation. They measure 2010 segregation for MSAs with over 500,000 people using the aspatial Reardon and O'Sullivan (2004) ordinal information theory index that compares the percent difference in MSA income diversity and a population-weighted sum of each block group's income diversity.[4] They run OLS with controls using the 2005 Wharton Residential Land Use Regulation Index (WRLURI) survey of 11 categories of local land use regulations from Gyourko et al. (2008).

However, their identification strategies may be inadequate to establish causality, and their segregation measures do not account for the socioeconomic composition of nearby neighborhoods. This paper, like Lens and Monkonnen (2016), uses the Wharton Residential Land Use Regulation Index (WRLURI) that surveys 1,904 jurisdictions in 293 MSAs, instead of the Pendall land use regulation survey that Rothwell and Massey (2010) uses, to increase the number of observations. I extend the work of these papers in two ways. First, I use more convincing instrumental variables (IVs). Second, I use additional measures of MSA-level segregation that capture the geographic distance between neighborhoods, using Census block group as a proxy for neighborhood.

[4] See the Methods section below for a formal discussion of segregation measurement.

My primary specifications measure MSA residential segregation by income using the spatial ordinal information theory index, from Reardon et al. (2006). The index relies on 2012-2016 5-year ACS block-level Census data and the NBER block group distance database for the 2010 US Census. I estimate the causal effect of MSA-level averages of municipal WRLURI scores on this segregation measure using 2SLS. Because historical segregation patterns and other factors likely influence both 2005 land use regulation and 2012-2016 segregation, I instrument for land use regulation using the 1982 share of protective inspection and regulation expenditures from the US Census of Governments and 1991 stream count from the US Geological Survey (USGS) (Dawkins 2005, Saiz 2010). 1982 protective expenditure share proxies an MSA's historical political affinity for regulation in general, which should predict land use regulation and is otherwise plausibly unrelated to segregation. 1991 stream count proxies an MSA's geographic fragmentation, assumed to affect segregation only through its contribution to political fragmentation and land use regulation. I also estimate the causal effect of WRLURI on the spatial information theory index of Black-White segregation.

This paper's main contribution is finding that land use regulation, measured by WRLURI, reduces MSA segregation by income under a range of measures that incorporate geographic distance between block groups. Heterogeneous effects across WRLURI components suggest differential effects by the type of land use regulation. Approval Delay and State Political Involvement Indexes reduce segregation, whereas the number of local bodies required to approve zoning changes increases segregation at all but the smallest spatial scales. The Density Restriction Index is positively associated with segregation but only significant in ordinary least squares (OLS) specifications.

In sum, prior empirical findings show land use restrictions, particularly on density, increase residential segregation by income and race (Berry 2001; Rothwell and Massey 2009, 2010; Rugh and Massey 2014; Lens and Monkkonen 2016). Closely building on Lens and Monkonnen (2016) and Rothwell and Massey (2010), this paper applies distance-based spatial segregation measures that better reflect effective segregation of economic opportunity and an alternative identification approach to address endogeneity. This paper finds overall land use regulation reduces MSA segregation. However, results vary by the measure of segregation and type of land use regulation.

Section 2 describes my methodological framework, identification strategy, and segregation measures. Section 3 describes my data. Section 4 reports the results. Section 5 concludes.

1.2 Methods

1.2.1 Empirical Framework

The empirical framework closely follows Rothwell and Massey (2010) and Lens and Monkonnen (2016). The empirical specifications regress MSA-level segregation variables from the 2016 5-year ACS on the 2005 Wharton Residential Land Use Regulation Index (WRLURI). The lag between 2005 and 2012-2016 provides time for land use regulations to affect residential segregation. My controls are mostly from the 2000 Census to avoid errors cross-walking from 2016 to the 2000 MSA boundaries that WRLURI uses. I first follow the main regression from Lens and Monkonnen (2016), except I use ACS 2012-2016 segregation data instead of 2010 data and I do not drop MSAs with fewer than 500,000 people.

I use the model:

$$S_i = \beta_0 + \beta_1 R_i + \boldsymbol{X}_i \beta_2 + u_i$$

where i is MSA (2000 Census MSA/PMSA). S is a measure of segregation by household income, the ratio of household income to the poverty threshold, or race. R is the score for WRLURI or one of its components. $\boldsymbol{X}$ is a vector of controls: the natural log of the MSA's total population (2000 Census), the Gini Index of Income Inequality (ACS 2016 5-year), the share of households with annual household income less than $20,000 (2000 Census), the share of households with annual household income at least $60,000 (2000 Census), the share of the total population who is Black alone or Hispanic alone (2000 Census), and the number of general purpose municipality governments (e.g. cities and townships) in 2002.

1.2.2 Identification

Land use regulation may be endogenous because past segregation and other variables may influence both an MSA's land use policy and current segregation. Both land use regulations and residential segregation by race and income persist over time. Many of the first zoning codes in the 1910s explicitly required racial segregation, reflecting preferences for segregation that likely shaped both modern segregation and modern zoning codes. This paper seeks to address this concern with instrumental variables that plausibly affect land use regulation but not segregation except through the covariates in the model.

Rothwell and Massey (2010) instrument for land use regulation with year of statehood and 1910 population density, which the authors suggest proxy for MSAs with more established suburban settlements that would typically restrict land use more than would new settlements. Rothwell and Massey (2010) observe that MSAs with later statehood year tend to have had less time for rural settlements to form around cities. They hypothesize older rural settlements are more likely to have established political coalitions opposing new development, citing Olson (1982). Such settlements may be more prevalent in historically denser MSAs. They observe zoning restrictiveness measured by a zoning survey has a strong negative correlation with statehood year and positive correlation with 1910 population density, consistent with this hypothesis. To be valid, 1910 population density and statehood year must only affect segregation via channels captured by variables included in the regression model.

While statehood year and 1910 population density mostly predate the adoption of zoning and other modern land use regulations, these instruments may not be valid if MSAs in older states or with higher 1910 population densities are systematically more or less prone to segregation through channels outside land use policy such as their effect on modern population density.[5] Statehood year may be invalid if it proxies for historical racial segregation. 1910 population density of MSAs may be subject to bias from endogenous MSA boundaries. For instance, an MSA in California includes predominantly rural Kern County, one of the geographically largest counties in the US. By contrast, New England MSAs define boundaries by municipalities rather than counties. New England MSAs are thus more likely to exclude rural areas and, in turn, will appear denser than in other states.

Instead, my preferred MSA-level instrumental variables for WRLURI are 1982 protective regulation and inspection expenditure share from Saiz (2010) and number of stream segments in the 1991 USGS hydrography layer from the 1:2,000,000 DLG data from Dawkins (2005). Dawkins (2005) and Hoxby (2000) employed number of streams as an instrument for municipal competition on segregation. They note that streams acted historically as geographic barriers, contributing to political fragmentation within an MSA.

[5] Rothwell and Massey (2010) include population density as a control in their initial regression with extensive controls before pairing down to their preferred parsimonious regression.

Political boundaries often formed along streams, especially in the 19th century when even small streams posed significant transportation barriers. Thus, areas with a greater number of streams would be more likely to have a greater number of municipal jurisdictions. This greater number of jurisdictions would also create greater incentive for local regulation attempting to capture local land rents within an MSA and free ride as much as possible on surrounding neighborhoods by restricting their own land use. Accordingly, the number of governments is positively associated, albeit loosely, with land use regulation.

Because the number of jurisdictions could affect segregation, I control for the number of jurisdictions. Controlling for number of governments, more streams within a given municipality posed historical barriers to forming municipality-wide political coalitions to advocate for land use restrictions. An abundance of river amenities also reduces a municipality's potential property value gains from restricting residential density. The number of streams is negatively correlated with land use regulation, albeit modestly (-.14). Even after controlling for the number of jurisdictions, the number of streams is negatively associated with WRLURI.

If the geographic barriers and variation of natural amenities created by rivers within an MSA influenced initial settlement or intensify segregation through channels not included in my model, the instrument is invalid. But Cutler and Glaeser (1997) find no significant correlation between the number of streams and segregation after controlling for the number of jurisdictions. Hence, it seems plausible that the number of streams is unrelated to segregation except through land use regulation and my controls.

Additionally, I use local public protective inspection and regulation expenditures as a share of local government revenues from the Census 1982 State and Local Government Finance Data.[6] Saiz (2010) argues this local government spending allocation may proxy for historical local preference for government regulation independent of housing preferences. He notes that this category covers regulation of financial institutions, professional occupations, liquor, and various other economic activities in addition to buildings and land use. He uses the variable to instrument for WRLURI in housing elasticity regressions. Protective expenditure share correlates positively with WRLURI. Segregation may be related to the levels of public expenditures as a reflection of willingness and capacity to provide public goods and services. However, the share of local public revenues spent on regulation disconnects the measure from the aggregate size of public spending. Thus, it seems plausible that the public protective inspection and regulation expenditures as a share of public revenue is not related to segregation except through land use regulation.

1.2.3 Measurement of Segregation

My specifications include spatial and aspatial versions of the information theory indexes for household income, poverty ratio, and race. For each of the spatial information theory indexes, I run specifications with measures at 500, 1000, 2000, 4000, and 8000 meter radii.[7] My preferred measure is the spatial ordinal information theory index of household income segregation.[8] To

[6] The US Census Bureau defines protective inspection and regulation as "regulation of private enterprise for the protection of the public and inspection of hazardous activities except for major functions, such as fire prevention, health, natural resources, etc."

[7] Chetty et al. (2020) find characteristics of blocks only within a mile of a child's block help explain a child's future earnings. Smaller spatial scales like 500m matter more for those with restricted mobility like young children and the elderly. Intermediate spatial scales like 2000m may be more important for teenagers. Larger distances may matter more for mobile working-age adults.

[8] Massey and Denton (1988) identify five dimensions of segregation: evenness, exposure, concentration, centralization, and clustering. Reardon and O'Sullivan (2004) condense all five dimensions into two broader dimensions: spatial evenness and spatial exposure. Spatial evenness reflects how similarly different population

build this index, I will first describe an aspatial information theory index H and move on to a spatial information theory index $\widetilde{H}$. I will then describe how to move to an aspatial ordinal information theory index H_O and Reardon's spatial ordinal information theory index $\widetilde{H}_O$.

The aspatial information theory index measures how different the population composition of an MSA is as an aggregate unit of geography relative to its constituent block groups. I will always be comparing two groups *m*: either the share White vs. share Black or the share above vs. share below income threshold *t*. The building block for the difference between the population composition of an MSA and its constituent block groups is a population diversity measure called the Entropy Diversity Index:

$$E = \begin{cases} \sum_{m=1}^{2} \frac{P_m}{\sum_{n=1}^{2} P_n} \ln \frac{\sum_{n=1}^{2} P_n}{P_m} \text{ if } 0 < \frac{P_m}{\sum_{n=1}^{2} P_n} < 1 \\ 0 \text{ otherwise} \end{cases} \quad (1)$$

and

$$E_j = \begin{cases} \sum_{m=1}^{2} \frac{P_{jm}}{\sum_{n=1}^{2} P_{jn}} \ln \frac{\sum_{n=1}^{2} P_{jn}}{P_{jm}} \; if \; 0 < \frac{P_{jm}}{\sum_{n=1}^{2} P_{jn}} < 1 \\ 0 \; otherwise \end{cases} \quad (2)$$

where *E* is the Entropy Diversity Index for the overall MSA, E_j is the aspatial Entropy Diversity Index for sub-area unit (e.g. Census block group) *j* within the MSA, *m* and *n* are sub-population categories where $m, n = 1$ is the relatively disadvantaged group (e.g. below income threshold t)

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groups distribute across residential space within a metro area. Spatial exposure reflects how prevalent members of one population group are in the residential space near a member of another group.

My main specifications use the spatial ordinal information theory index from Reardon et al. (2006), a weighted average of binary-group segregation values (Reardon 2011). The spatial information theory index captures spatial evenness. It builds on the aspatial Theil's H Information Theory Index (Reardon et al. 2018). Reardon (2011) demonstrates its robustness to income category thresholds for US MSAs if using all Census income bins and to the set of income bins if bins span most of the income distribution.

and $m, n = 2$ is the relatively advantaged group (e.g. above income threshold t), P_m is the MSA's population in sub-population category *m* (e.g. MSA population below income threshold *t*), and P_{jm} is sub-area unit *j*'s population in category m. When $E = 0$ or $E_j = 0$, the MSA or sub-area unit, respectively, only has people from one of the two sub-population categories. The larger the value of *E* or E_j (up to a maximum of 1), the more equal are the population shares of categories $m = 1$ and $m = 2$ within the MSA or sub-area unit, respectively.

The Information Theory Index *H* is:

$$H = 1 - \frac{\sum_{j=1}^{J} \frac{P_j}{P} E_j}{E} \quad (3)$$

where *J* is the number of sub-area units *j* in the MSA. The Information Theory Index ranges from zero to one. When $H = 0$, knowing the block group a person lives in is no more informative about the person's likelihood of belonging to category *m* than is knowing the person's MSA. When $H = 1$, knowing the block group a person lives in fully informs you about the category *m* to which a person belongs. This binary form of the information theory measure (i.e. *m* has two possible values) provides both my measure of Black-White segregation and the components for my primary aspatial measure of income segregation.

Spatial versions of the information theory index reflect how informative knowing a person lives within radius *r* of a Census block group *j* is for knowing the category *m* to which the person belongs. The Spatial Ordinal Information Theory Index $\widetilde{H}$ accounts for the population composition of nearby sub-area units up to some radius distance *r* (e.g. 500m). This is done by creating a Spatial Entropy Diversity Index $\widetilde{E}_j$ for each sub-area unit *j* using proximity-based weights:

$$w_{jk} = \begin{cases} \left[1 - \left(\frac{d_{jk}}{r}\right)^2\right]^2 & if\ d_{jk} < r \\ 0\ otherwise \end{cases} \quad (4)$$

for every combination of sub-area units *j* and *k* where d_{jk} is distance in miles between the internal points of sub-area units *j* and *k*. For each group m in each sub-area *j*, there is a spatially weighted local population composition (LPC) function:

$$LPC_{jm} = \frac{\sum_{k \in J} P_{km} \times w_{jk}}{\sum_{k \in J} (\sum_{n=1}^{2} P_{kn}) \times w_{jk}} \quad (5)$$

that divides the sum of all these weighted nearby-sub-area populations in group *m* by the weighted sum of the population overall. The Spatial Entropy Diversity Index for each *j* is then:

$$\tilde{E}_j = \begin{cases} \sum_{m=1}^{2} LPC_{jm} \ln \frac{1}{LPC_{jm}} & if\ 0 < LPC_{jm} < 1 \\ 0\ otherwise \end{cases} \quad (6)$$

Substituting $\tilde{E}_j$ into the information theory index gives the Spatial Information Theory Index:

$$\widetilde{H} = 1 - \frac{\sum_{j=1}^{J} \frac{P_j}{P} \tilde{E}_j}{E} \quad (7)$$

The binary form of $\widetilde{H}$ (i.e. *m* has two possible values) provides both my spatial measure of Black-White segregation as well as the components for my primary spatial income segregation measure, the Spatial Ordinal Information Theory Index. When $\widetilde{H} = 0$, knowing the block group a person lives in is no more informative about the likelihood a neighbor belongs to category *m* than is knowing the person's MSA. When $\widetilde{H} = 1$, knowing the block group a person lives in fully informs you about the category *m* to which a neighbor belongs. Neighbors include anyone in the same block group and a proximity-weighted share of people in other block groups within a specified radius (500m, 1000m, 2000m, 4000m, or 8000m).

To measure income segregation for my aspatial baseline specification, I use the Ordinal Information Theory Index H_O (Reardon 2011, Lens and Monkkonen 2016). Here, the sub-area units *j* are Census block groups, and the sub-population categories $m = 1{,}2$ are the groups above and below an income threshold *t*. That is, equation (3) provides H_t for a given income threshold. Then,

$$H_O = \sum_{t=1}^{T} \frac{E_t H_t}{\sum_{u=1}^{T} E_u} \quad (8)$$

is a weighted average of H_t across all income thresholds *t*.[9] To measure income segregation for my spatial specifications, I use the Spatial Ordinal Information Theory Index $\widetilde{H}_O$:

$$\widetilde{H}_O = \sum_{t=1}^{T} \frac{E_t \widetilde{H}_t}{\sum_{u=1}^{T} E_u} \quad (9)$$

that is simply the spatial analog of H_O.

1.3 Data

1.3.1 Dependent Variables: Aspatial and Spatial Segregation Measures

This paper's dependent variables are MSA-level segregation measures created from ACS 5-year 2016 block group and the NBER Census Block Group Distance Database data crosswalked

[9] For my measures, H_t are binary-group indices of segregation of those above income threshold *t* from those below income threshold *t*. The two categories *m* are: (1) population above and (2) population below some income threshold *t*. H_t calculates how closely each block group's population shares above and below income threshold *t* match those of the overall MSA. It sums these values of each block group in the MSA weighted by the block group's share of the MSA's population. H_O aggregates all values of H_t for each *t*, weighted by the value of E_t, which increases the closer *t* is to the 50th percentile in the MSA population. E_t (E_u) is the Entropy Diversity Index *E* where the two categories *m* are: (1) population above and (2) population below some income threshold *t* (*u*).

to 1999 MSA and PMSA boundaries of 295 MSAs and PMSAs.[10,11] Each regression employs a version of the information theory index to capture the evenness or spatial evenness dimension of segregation. Relative segregation between MSAs varies with scale, but Table 1 shows that the correlation across scales within each measure always exceeds .75.

Ordinal Information Theory Index for Poverty: I use the Stata "rankseg" command to create an ordinal information theory index (equation 8) using population counts of bins for people with income in the following percentage ranges of the poverty threshold: 0-49%, 50-99%, 100-124%, 125-149%, 150-184%, 185-199%, and 200%+. Hence, this ordinal index is a weighted sum of six information theory indexes (one for segregation of people with household income above from people with household income below each of the following percentages of the poverty line: 50%, 100%, 125%, 150%, 185%, and 200%).

Ordinal Information Theory Index for Income: I use the Stata "rankseg" command to create an ordinal information theory index (equation 8) using number of household counts of bins for the following 16 household income ranges: $0-9,999, $10,000-14,999, $15,000-19,999,

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[10] ACS 5-year 2016 block group population counts are not adjusted to ensure they match official population estimates. US Census encourages using ACS block group data only to compare percentages and averages, not population or sub-group population counts. However, my segregation measures rely on these population counts and are susceptible to significant measurement error. See: https://www.census.gov/programs-surveys/acs/guidance/handbooks/researchers.html.

[11] I use Metropolitan Areas from 1999 defined by the Office of Management and Budget (OMB) under a complex set of standards (see: https://www.govinfo.gov/content/pkg/FR-1998-12-21/pdf/98-33676.pdf#). Typically, a metropolitan area includes central counties (cities/towns only in New England) containing most of a city or urbanized area of at least 50,000 people and outlying counties (cities/towns only in New England) with any of the following: (1) at least 50% of employed residents commuting into the central counties and at least 25 people per sqmi; (2) 40%+ commuting and 35+ per sqmi or 5000+ residents live in qualifier urbanized area; (3) 25%+ commuting and 50+ per sqmi or two of following: (a) 35+ per sqmi, (b) 35% urban population, (c) 5000+ in qualifier urbanized area; (4) 15%+ commuting (or workers commuting from central counties is 15%+ and all workers commuting to and from central counties if 20%+ of employed residents) and two of following: (a) 60+ per sqmi, (b) 35% urban population, (c) 20%+ population growth between last decennial censuses, (d) 5000+ in qualifer urbanized area; (5) 2500+ residents live in central city. This paper refers to both MSAs (metropolitan statistical areas) and PMSAs (primary metropolitan statistical areas) as MSAs.

$20,000-24,999, $25,000-29,999, $30,000-34,999, $35,000-39,999, $40,000-44,999, $45,000-49,999, $50,000-59,999, $60,000-74,999, $75,000-99,999, $100,000-124,999, $125,000-149,999, $150,000-199,999, and $200,000+. Hence, this ordinal index is a weighted sum of 15 information theory indexes, one for segregation of households with income above from households with income below each of the following income thresholds: $10,000, $15,000, $20,000, $25,000, $30,000, $35,000, $40,000, $45,000, $50,000, $60,000, $75,000, $100,000, $125,000, $150,000, and $200,000.

Black-White Information Theory Index for Race: For the simpler non-ordinal information theory indexes, I use Reardon and Townsend's "seg" command for a Theil's *H* (equation 3) for racial categories White non-Hispanic and Black non-Hispanic (Reardon 2011, Reardon et al. 2018).

Spatial Ordinal Information Theory Indexes for Poverty and for Income: Following Reardon et al (2006), I create separate indexes (equation 9) that account for the population composition of nearby block groups up to each of the following radii *r*: 500m, 1000m, 2000m, 4000m, and 8000m.[12]

Spatial Black-White Information Theory Indexes for Race: I adopt the spatial information theory index in equation 7, calculating spatial versions of the Black-White

[12] The "rankseg" command doesn't include a spatial option, so I create spatial-adjusted ordinal bins. First, I create the proximity-based weight function w_{jk} for every combination of block groups *j* and *k* (equation 5). For each group *m* in each block group *j*, I create the spatially-weighted local population composition (LPC) function LPC_{jm} that divides the sum of all these weighted nearby-block-group populations in group *m* by the sum of weighted nearby-block-group populations overall. LPC_{jm} multiplied by block group *j*'s population then serve for the spatial-adjusted ordinal bins when I run "rankseg" command by MSA with order zero to create MSA-level spatial ordinal information theory indexes. Correlations between spatial indexes and the aspatial index are decreasing in the radius the spatial index uses (from 0.98 with the 500m radius to 0.76-0.77 with the 8000m radius). Index values generally decrease with spatial scale but much more in some MSAs than in others, suggesting income distribution across neighborhoods changes more sharply in some MSAs than in others.

information theory measures of racial segregation above using the spatially weighted LPC function to weight the aspatial racial population counts in the information theory equation.

1.3.2 Key Explanatory Variables: Land Use Regulation Measures

The 2005 Wharton Residential Land Use Regulation Index (WRLURI) proxies for land use regulation. Gyourko, Saiz, and Summers (2008) discusses their 2005 survey of municipal Planning Directors or Chief Administrative Officers on residential land use regulation in 2,649 municipalities in the United States. Gyourko provides weights to aggregate the index into a 1999-MSA-level dataset, which I use (dropping municipalities outside year-1999 MSAs).[13] WRLURI decomposes into the following 11 subindices.

Local Political Pressure Index (LPPI) assesses the importance for "residential building activity and growth management" of local and county government, community pressure, city budget constraints, school crowding, opposition to growth, and local land conservation initiatives. Local political pressures may be a response to recent local population growth and diversification that I expect would slow future growth and integration. County government importance may affect segregation more at a larger between-municipality spatial scale than do city council, city budget constraints, and city council opposition to growth. School crowding may increase segregation between school districts and school zones. I expect community pressure and citizen opposition to growth to primarily increase segregation at the smallest neighborhood spatial scales. Local land conservation ballot measures may reduce intra-jurisdiction segregation if open space protection makes affluent more willing to live in denser mixed-income neighborhoods, but otherwise may increase intra- or inter-jurisdictional segregation as lower

[13] WRLURI data are available as of April 2020 at http://real-faculty.wharton.upenn.edu/gyourko/land-use-survey/.

income families who can't afford housing adjacent to open space amenities sort into outlying communities by proximity to amenities.

State Political Involvement Index (SPII) reflects both the adoption of new statewide land use restrictions 1995-2005 and state legislative involvement in local "residential building activity and growth management." New state land use restrictions likely slow not only housing growth but also neighborhood sorting, implying ambiguous segregation effects, because state governments may favor more inclusionary restrictions and statewide restrictions raise development costs in both new and old neighborhoods. I expect that state involvement generally reduces segregation at larger spatial scales, but that specific state environmental rules and growth management policies vary widely in their effects.

State Court Involvement Index (SCII) captures the tendency of state appellate courts to uphold municipal land use regulations. I expect this empowers municipalities to impose exclusionary zoning, reinforcing segregation across all spatial levels.

Local Zoning Approval Index (LZAI) reflects the number of local bodies required to approve any zoning change request. Local Planning Approval Index (LPAI) reflects the number of local bodies required to approve a project. Local Assembly Index (LAI) is an indicator for certain New England localities that require popular approval at an open town meeting for any zoning change. Added barriers to new and higher density housing likely reinforce segregation but could potentially slow neighborhood transitions toward segregation, particularly at smaller spatial scales.

Supply Restriction Index (SRI) reflects the presence of statutory limits on the number of building permits, number of units authorized per year, total number of multifamily dwellings, and number of units per multifamily building. I expect restricting total multifamily dwellings and units per multifamily building, by limiting housing density and mix, increases macro-segregation between high and low demand regions within growing MSAs. Limiting building permits and units authorized per year likely slows both new housing growth and neighborhood sorting, implying an ambiguous expected effect on segregation.

Density Restriction Index (DRI) is an indicator for having a one-acre minimum lot size requirement. I expect minimum lot size increases segregation by limiting both maximum housing density and affordable housing options.

Open Space Index (OSI) is an indicator for having open space requirements. Requiring lots to dedicate some portion for open space limits development options. Housing costs will rise on lots with open space rules. But neighborhoods that preserve open space amenities without explicitly limiting housing may be more amenable for the affluent to live and still permit lower income housing options.

Exactions Index (EI) is an indicator for having exactions on developers for a share of infrastructure costs related to the development. Exactions reduce new housing growth, but paying the cost of additional infrastructure may deter new developments segregated from other neighborhoods, with effects likely at larger spatial scales.

Approval Delay Index (ADI) captures the expected number of months between application and receipt of building permit. A slower permitting process raises fixed costs making some affordable housing projects financially infeasible, likely increasing segregation, but it could also slow neighborhood sorting, potentially extending a neighborhood transition period between segregated equilibrium states.

1.3.3 Control Variables

From decennial US Census 2000 SF1 and SF3 data files at the MSA level, I obtain the following MSA-level control variables: natural log of total MSA population in 2000, share of total MSA population who is Black only or Hispanic only, share of total MSA households with annual household income less than $20,000, and share of total MSA households with annual household income $60,000 or more.[14] The Gini Index of Inequality measure of MSA income inequality comes from ACS 5-year 2016 MSA-level data crosswalked to year-2000 MSAs and PMSAs. specified radius (500m, 1000m, 2000m, 4000m, or 8000m).

MSA-level number of municipal jurisdictions in 2002 comes from a list of local government jurisdictions from the 2002 Census of Governments (COG). I create a count variable equal to the number of municipalities (cities, townships, etc.), which excludes county, school district, and other non-general-purpose municipal governments. Joint city/county governments like San Francisco count only once, and separate county governments don't count at all. I attempt to follow Rothwell and Massey (2009, 2010) and Lens and Monkonnen (2016) in this definition. However, I multiply the number of municipalities by the number of general purpose governments. The 2002 COG file identifies a municipality's county but not MSA, so I use the Missouri Census Data Center's Geocorr program to match year-2000 counties to year-2000 MSAs and PMSAs. The final variable reflects the mean of the product of the number of municipalities and number of general purpose governments within each county in the MSA.

[14] I use year-2000 data instead of ACS 5-year 2012-2016 data due to challenges with crosswalking data from 2012-2016 boundaries to 2000 boundaries. Since I'm not concerned with a causal interpretation for these control variables, I would prefer 2012-2016 estimates for all variables to more precisely capture potential sources of variation in segregation outside of land use regulation but would need a more precise crosswalk.

1.3.4 Instrumental Variables

MSA-level 1982 Local Public Protective Inspection and Regulation Expenditures as a Share of Total Local Public Revenues comes from 1982 Census State and Local Government Finance Data at the individual jurisdiction level. I crosswalk these year-1982 jurisdictions into year-2000 MSAs. Dividing MSA-level total protective expenditures by MSA-level total revenues produces a protective expenditure share variable.

MSA-level Number of Stream Segments, following Dawkins (2005), come from joining the 1991 USGS 48-state hydrography layer from 1:2,000,000-scale DLG data to NHGIS 2000 MSA boundary data in ArcGIS Pro. For each MSA, I count the number of stream segments at least 1km in length.

1.4 Results

1.4.1 Information Theory Index of Income Segregation: WRLURI

The Tables 2 and 3 present results for how overall land use restrictiveness affects different measures of residential segregation by income. Table 2 measures residential segregation of households by household income level. Table 3 measures residential segregation of households by the ratio of household income to poverty threshold. Information theory index measures of segregation can range from zero under no segregation to one under complete segregation. Each table displays results of both OLS (odd columns) and IV (even columns) estimates for an aspatial (columns 1 and 2) and five spatial measures differing in the radius of their distance-based population weights: 500 meters (columns 3 and 4), 1000 meters (columns 5 and 6), 2000 meters (columns 7 and 8), 4000 meters (columns 9 and 10), and 8000 meters (columns 11 and 12).

Table 2 shows economically and statistically significant negative effects of WRLURI on the Information Theory Index measure of household income segregation in all specifications except only marginally statistically significant in the aspatial (OLS and IV) and the 500m radius (OLS) specifications. Both precision and magnitude of estimates increase with spatial scale. The variance across MSAs in income segregation decreases as spatial scale increases. Standardized point estimates for WRLURI attenuate almost proportionally up to the 4000m spatial scale. IV estimates roughly tripled the OLS coefficient estimate magnitudes. The IV is strong (F=18.7), underidentification is rejected, and the null of exogenous instruments is not rejected.

For IV results, a standard deviation increase in WRLURI decreases household income segregation 0.31 standard deviations (at the aspatial scale), 0.38 standard deviations (at the 500m radius scale), 0.49 (1000m), 0.62 (2000m), 0.73 (4000m), and 0.72 (8000m). This implies an increase in restrictiveness of land use regulation in St. Louis MSA from the 25th percentile to the 75th percentile (just below Riverside) would reduce segregation 10% from the 76th to the 60th percentile for the 500m radius (just below Las Vegas) and 25% from 86th to 56th percentile for the 4000m radius (slightly below Oakland).

Table 3 presents results for the indices of segregation by ratio of a person's income to the poverty threshold. Coefficient estimates are also negative but about 30-50% smaller and only statistically significant for 2000m, 4000m, and 8000m spatial scales (1000m was marginally significant). For IV results, a standard deviation increase in WRLURI decreases poverty ratio segregation 0.14 standard deviations (at the aspatial scale), 0.20 standard deviations (at the 500m radius scale), 0.28 (1000m), 0.40 (2000m), 0.49 (4000m), and 0.46 (8000m). Again, the IV is strong (F=18.7), underidentification is rejected, and the null of exogenous instruments is not rejected.

1.4.2 Information Theory Index of Income Segregation: WRLURI Components

Individual components of WRLURI have associations with the information theory index of segregation by household income (Table 4) and by poverty ratio (Table 5) of varying signs, magnitudes, and significance. State involvement and approval delay appear to drive the overall negative effect of WRLURI; other types of regulation, such as residential density restrictions (lot area minimums) and local zoning approval complexity, may increase segregation. Open space requirements also may reduce segregation. Unlike findings in Lens and Monkonnen (2016), local political pressure and local project approval complexity appear to reduce rather than increase income segregation, at least at higher spatial scales.

Local Political Pressure Index (LPPI): LPPI has a statistically significant negative association with all the indices of household income segregation (except only marginally significant for 500m radius and for aspatial) but only in IV estimates, which suffer from weak instruments (F=3.9) such that true standard errors may be larger. LPPI is especially vulnerable to endogeneity because it captures current public attitudes toward land use regulation issues and is much more likely determined by recent conditions. IV magnitudes range from 11 (aspatial) to 180 (2000m) times as large as the positive and insignificant OLS estimates. A one unit increase in LPPI reflects municipalities in an MSA increasing local political pressure by a standard deviation on average. For IV specifications, a standard deviation increase in LPPI reduces household income segregation by between .71 (aspatial) and 1.55 (8000m radius) standard deviations.

State Political Involvement Index (SPII): SPII has a statistically significant negative association with all aspatial and spatial levels of segregation by household income except only marginally significant for the 500m IV specification and insignificant for the aspatial IV specification. The IV is strong (F=15.2) but at the 500m scale nearly rejects the null of excludability with a 0.07 Hansen J p-value. The aspatial IV estimate is just 12% larger in magnitude than the OLS estimate, but spatial IV estimates are 24% (500m) to 104% (8000m) larger in magnitude. A unit increase in SPII translates to state political involvement increasing in an MSA's municipalities by a standard deviation on average. IV results imply a standard deviation increase in SPII decreases aspatial segregation 0.25 standard deviations. Point estimates increase in magnitude with spatial scale from 0.29 (500m) to 0.62 (8000m) standard deviations.

SPII has a statistically significant negative association with segregation by poverty ratio in all specifications except only a marginally significant negative effect for the 1000m spatial scale IV specification and no significant effect for 500m and aspatial IV specifications. Magnitudes are generally similar across all spatial scales in OLS, with a standard deviation increase in SPII associated with a 0.22 (aspatial) to 0.27 (4000m) standard deviation decrease in segregation by poverty ratio. However, in IV specifications, magnitudes range from 0.11 (aspatial) to 0.42 (4000m) standard deviations.

State Court Involvement Index (SCII): SCII has no statistically significant association with income segregation except a marginally significant negative effect for household income segregation at the 4000m radius in the IV specification. Moreover, the IV's null of excludability is rejected in all SCII specifications ($p<0.05$) except segregation by poverty ratio at the aspatial, 500m, and 1000m scales.

Local Zoning Approval Index (LZAI): LZAI, an MSA's average number (0-6) of government bodies required to approve a local zoning change, has a statistically significant positive association with household income segregation in all specifications except only marginally significant at the 500m spatial scale in IV. Poverty ratio segregation is statistically significant in OLS at 500m, 1000m, and 8000m scales but only marginally significant at 2000m and 4000m scales. Poverty ratio segregation is statistically significant in IV for 2000m, 4000m, and 8000m scales. LZAI coefficient estimates are always positive, but IVs are weak at explaining variation in LZAI (F=3.4). OLS point estimates imply a standard deviation increase in LZAI is associated with an increase of 0.10-0.14 standard deviations in segregation. However, IV point estimates imply a standard deviation increase in LZAI increases segregation by household income 0.84 (aspatial) to 1.95 (4000m) standard deviations and segregation by poverty ratio 0.36 (aspatial) to 1.26 (8000m) standard deviations.

Local Project Approval Index (LPAI): LPAI, an MSA's average number (0-6) of government bodies required to approve a local project, has a statistically significant positive association in OLS with segregation by poverty ratio at aspatial, 500m, and 1000m scales. LPAI has a marginally statistically significant positive association in OLS with 2000m-scale segregation by poverty ratio and with aspatial-, 500m-, 1000m-, and 2000m-scale segregation by household income. Using IV, LPAI has a statistically significant negative association only with 8000m-scale by household income and marginally significant negative association with segregation by household income across aspatial and all spatial scales and with 8000m-scale segregation by poverty ratio. IVs provide fairly weak identification with an F-statistic of 4.5.

Using OLS, a standard deviation (s.d.) increase in LPAI is associated with an increase of 0.13 (aspatial, 500m, and 1000m scales) and 0.11 (2000m) s.d. in segregation by poverty ratio and 0.09 (aspatial and 2000m scales), 0.10 (500m), and 0.11 (1000m) s.d. by household income. But using IV, the sign changes from positive to negative with an s.d. increase in LPAI associated with a decrease ranging from 0.57 (aspatial) to 1.08 (8000m) s.d. in segregation by household income and 0.82 s.d in 8000m-scale segregation by poverty ratio. If IVs are valid, this suggests added project approval veto points may either passively prolong transitional periods of neighborhoods sorting from one socioeconomic group to another or actively promote socioeconomic diversity in residential development, at least at larger spatial scales.

Local Assembly Index (LAI): LAI has no statistically significant association with the information theory index of income segregation.

Density Restriction Index (DRI): DRI, an MSA's share of municipalities with a one-acre minimum lot size for some lots, in OLS has a statistically significant positive association with the index of household income segregation across aspatial and all spatial scales and marginally significant positive association with aspatial-, 2000m-, and 4000m-scale poverty ratio segregation. IV results are also always positive but marginally significant only for 2000m- and 4000m-scale household income segregation. IV is weak (F=2.3) in all DRI specifications. Excludability is rejected ($p<0.03$) at all scales for household income segregation and at the 8000m scale for poverty ratio segregation. Using OLS, a standard deviation increase in DRI is associated with a 0.12-0.16 s.d. increase in household income segregation and a 0.08-0.11 s.d. increase in poverty ratio segregation. Using IV, a standard deviation increase in DRI is associated with a 1.15 (2000m scale) and 1.38 (4000m scale) s.d. increase in household income segregation.

Open Space Index (OSI): OSI, an MSA's share of municipalities with open space requirements, has a negative and significant association with household income segregation in all spatial scales (only marginally significant at 500m scale) using IV and in only 8000m scale using OLS. OSI also has a negative and significant association with 4000m-scale poverty ratio segregation and marginally significant with 2000m and 8000m scales, using IV. A standard deviation increase in OSI decreases household income segregation 1.08 s.d. (1000m scale), 1.36 s.d. (2000m scale), 1.61 s.d. (4000m scale), and 1.60 s.d. (8000m scale) using IV, about 20 times the magnitude using OLS. A standard deviation increase in OSI decreases poverty ratio segregation 1.07 s.d (4000m) using OLS. The IVs are weak with an F-statistic of 4.4.

Exactions Index (EI): EI, an MSA's share of municipalities that charge developers for public infrastructure expenses associated with their project, only has a statistically significant association with the 4000m-scale household income segregation and only has a marginally significant association with the 2000m-scale household income segregation, using IV. A one standard deviation increase in EI is associated with a 0.70 s.d. decrease in 4000m-scale household income segregation. However, IV is weak (F=4.4), and excludability is rejected ($p<0.05$) at all scales for household income segregation. EI's coefficients are negative at all scales using IV but usually positive using OLS. EI has a positive and marginally significant association with aspatial household income segregation using OLS.

Supply Restrictions Index (SRI): SRI, an MSA's municipalities average number (0-6) of types of restrictions on the quantity of new housing units, has a marginally significant negative association with all spatial indices of household income segregation. IV point estimates would indicate a standard deviation increase in SRI decreases spatial household income segregation 0.75 s.d. (500m), 1.00 s.d. (1000m), 1.31 s.d. (2000m), 1.55 s.d. (4000m), and 1.50 s.d. (8000m). This weakly suggests permit supply caps may prolong periods of neighborhood transition from one socioeconomic group to another. But the IVs are weak with an F-statistic of 2.7, suggesting the true standard errors may be even larger.

Approval Delay Index (ADI): ADI, the average number of months for project approval, has a statistically significant negative association with household income segregation in all specifications. For segregation by poverty ratio, ADI is statistically significant and negative in all OLS specifications and at 2000m scale and above (marginally significant at 1000m) in IV specifications. IV magnitudes are 1.2-3.0 times as large as OLS point estimates. An s.d. increase in ADI decreases household income segregation 0.37 s.d. (aspatial), 0.44 s.d. (500m), 0.56 s.d (1000m), 0.71 s.d. (2000m), and 0.83 s.d. (4000m and 8000m). The IVs are strong with an F-statistic of 16.1. This suggests project delays may prolong neighborhood transitions from one socioeconomic group to another.

1.4.3 Information Theory Index of Black-White Segregation

Table 6 shows WRLURI also has an economically significant negative effect on Black-White segregation, with economic magnitude and precision increasing with spatial scale. WRLURI has a statistically significant negative association with Black-White segregation in all OLS specifications but only at 8000m and 4000m scales and marginally at the 2000m scale in IV regressions. All coefficients are small, but the spatial coefficient is 65% (2000m), 104% (4000m), and 150% (8000m) larger than the aspatial coefficient in the IV regressions. A standard deviation increase in WRLURI decreases Black-White segregation 0.34 s.d. (2000m), 0.42 s.d. (4000m), and 0.51 s.d. (8000m). IVs are overidentified and strong with an F-statistic of 18.7. Null of exogenous exclusion restrictions for IVs is not rejected.

1.5 Conclusion

The Residential segregation by income inhibits upward economic mobility. Land use regulation has a theoretically ambiguous effect on segregation. Prior empirical literature relies on IVs that may not be valid and ignores the spatial dimension of segregation. Using alternative IVs, my regression results indicate land use regulation, as measured by WRLURI, modestly reduces MSA residential segregation by income, as measured by the spatial information theory index. However, the results are heterogeneous in both sign and magnitude across types of land use regulation and in magnitude across measures of segregation. The analysis closely follows the Lens and Monkonnen (2016) regressions but uses different years of data, includes over 290 MSAs instead of just the 95 largest MSAs, includes dependent variables with different spatial scales, and includes instrumental variables. The findings of statistically significant and negative effects of WRLURI on spatial segregation, albeit with modest magnitudes, contrast with the insignificant results of Lens and Monkonnen (2016) for aspatial segregation.

Why does this paper find a significant negative effect of WRLURI on income segregation when Lens and Monkonnen (2016) found no significant effect for the overall WRLURI? Segregation measures accounting for nearby neighborhoods better capture the relationship than the aspatial measure. Additionally, the IVs may help address endogeneity by which some less segregated areas may choose to adopt less restrictive land use policies. Also, Lens and Monkonnen (2016) studied only MSAs with over 500,000 people, whereas this paper nearly tripled observations by including smaller MSAs for which regulations may have less effect on available housing supply. Future work could examine how labor demand, housing demand, and other metropolitan characteristics may interact with land use regulation to affect segregation.

Land use regulations appear to, on net, help counteract other market forces driving segregation by income within MSAs. Land use regulation may slow neighborhood sorting by income by containing development to already developed areas and making it more difficult for higher income residents to develop or redevelop areas to isolate themselves from lower income residents within a given MSA. WRLURI closely correlates with a Census tract's ratio of housing costs to upward mobility (Chetty et al. 2020). MSA-wide land use regulation may drive income sorting between highly regulated MSAs rather than within and also shift population growth toward less regulated MSAs. Future research should explore how much of the negative finding is explained by spillover effects between MSAs.

While spatial and aspatial income segregation have similar coefficient signs, point estimate magnitude rises with spatial scale, suggesting regulations overall are more likely to promote residential integration at broader levels (e.g. high school zone) than at narrower spatial scales. Future research could explore potential mechanisms like regulations' effects on neighborhood filtering and the size versus frequency of new residential development projects.

Segregation indices by poverty ratio do not capture variation in income for anyone earning more than 200% of the poverty threshold. Thus, weaker results for segregation by poverty ratio imply regulation plays a larger role in segregation of higher income households, at least for lower spatial scales, consistent with Lens and Monkonnen (2016)'s finding for aspatial segregation of high-income households.

Consistent with Lens and Monkonnen (2016), results are heterogeneous across subindices. Subindices roughly proxy different regulatory components in land use. Results suggest some types of land use regulations decrease (and others increase) residential segregation by income. Because each subindex specification relegates all other subindices into the error term, identification is more questionable. Future work should examine the causal effects of specific land use policies more thoroughly.

Nonetheless, this paper's findings indicate that increasing the state role in land use regulation can reduce income segregation within MSAs. Statewide political coalitions may be more likely than local political coalitions to prioritize affordable housing or neighborhood income diversity. Future research could examine states scoring highly in state involvement like Washington and

Oregon, which both require local governments to adopt comprehensive land use plans that include urban growth boundaries and affordable housing plans subject to state standards.

While state involvement and approval delay policies trade off reducing within-MSA segregation and increasing between-MSA segregation, other regulations like local zoning approval complexity and density restrictions may unambiguously increase segregation. Governments may want to reduce the number of veto points in their zoning approval process. Residential development that encourages income-diverse neighborhoods may require more flexible zoning. Fewer veto points could make it easier to negotiate terms of beneficial residential developments. Lastly, relaxing density restrictions like lot area minimums could make it possible for lower income people to live in neighborhoods with higher land values.

CHAPTER 2

How property tax assessment caps affect residential construction

2.1 Introduction

Real property taxes, a major source of revenue for state and local governments in the United States, are conventionally regarded as a relatively stable and efficient means of raising revenue (Augustine et al. 2009). However, property taxes diminish the financial security of cash-poor owners of appreciating property who face barriers to leveraging their property's equity. Property tax increases are associated with increased residential mobility and displacement of homeowners (Martin and Beck 2018, Shan 2010).

Property tax assessment caps are one of many policies state and local governments have adopted to mitigate tax-induced displacement (Haveman and Sexton 2008). These assessment limit policies set a ceiling on a property's taxable assessed value equal to some percentage of a base year taxable value, usually limiting the annual growth rate in a property's taxable value. Assessment growth limits ensure smaller, more predictable changes in taxable value, reducing the share of property taxes on rapidly appreciating property. This reduces the tax-price risk for property owners and helps cash-poor homeowners keep their appreciating homes if tax rates do not rise (Anderson 2012). However, these limits distort decisions on whether to move, whether to invest in property, and where to locate, by conditioning reassessment on changes in property ownership, improvements, or use (Cornia and Walters 2006, Dye and England 2010, Imrohoroglu et al. 2018).

Property tax assessment caps slow the growth in tax burden for owners of rapidly appreciating property (Augustine et al. 2009, Haveman and Sexton 2008, Twait 2011). As property appreciates over time, these caps can result in massive gaps between a property's taxable and market value. Property tax assessment limits redistribute the tax burden from eligible properties that rapidly appreciate to ineligible or slowly appreciating properties or other tax bases. Assessment limits on all real property shift the tax burden toward properties with higher turnover rates (e.g., residential property) and less appreciation. This feature of assessment caps creates an incentive to avoid actions that would reset the property's taxable value to market value. Conditions for resetting taxable value to market value vary but often include changes in property ownership, use, zoning, or size.

Past literature has generally found evidence that assessment caps that reset taxable value to market value when a property changes ownership reduce the frequency of property transactions and residential mobility (Wasi and White 2005, Ferreira 2010, Ferreira et al. 2011, Ihlanfeldt 2011, Skidmore and Tosun 2010). Wasi and White (2005) found that California's Proposition 13 property tax assessment cap increased the average tenure of homeowners by 6% between 1970 and 2000, with the effect increasing in the size of the subsidy. However, Sjoquist and Pandey (2001) found no evidence that the reduction in taxable assessed value from the assessment freeze in Georgia's Muscogee County reduced the probability of home sales in 1997. Empirical findings are mixed on whether property tax assessment caps reduce involuntary displacement among long-term homeowners in gentrifying areas (Ding and Hwang 2020, Martin and Beck 2018).

Assessment caps reduce residential mobility at least in part by creating a tax cost to moving that "locks in" property owners who may otherwise prefer to move (Ferreira et al. 2011). Assessment growth caps create a tax price gap between potential new and existing homeowners that reduces in-migration (Skidmore and Tosun 2010). In jurisdictions with assessment caps, the gap between market value and taxable value diminishes the probability of a home sale, particularly for single-family homes and low-tax jurisdictions (Ihlanfeldt 2011). Allowing homeowners to transfer the value of the assessment cap subsidy on their current home to a new home dramatically increases moving rates (Ferreira 2010). The lock-in effect emerges even in weak housing markets like Detroit, potentially exacerbated by upward bias in appraisals of tax officials (Hodge et al. 2015).

To the extent that actions triggering a reset to market value are associated with residential construction, assessment caps will reduce the likelihood of construction on highly appreciated property. Given the association between residential mobility and construction, reducing residential mobility may reduce correlated construction spending (Sexton 2010). However, assessment caps may also increase the relative demand for long-term homeownership in jurisdictions with caps by insuring against a property's future growth in taxable value (Anderson 2012). Furthermore, capping only residential taxable value growth creates an incentive to convert non-residential property to residential. Thus, the expected overall effect of assessment caps on residential construction is ambiguous.

Various property tax policies affect construction. Land value taxes appear to shift development from smaller structures in peripheral areas toward larger structures on higher-value urban parcels (Cho et al. 2010, Cho et al. 2013). Real property tax rates are associated with smaller lot areas, smaller house sizes, and larger house sizes per lot area (England et al. 2013).

Assessment caps may counteract these effects. Property transfer taxes encourage the purchase of cheap undeveloped land for new development and discourage property transfer toward the most efficient use (Brandt 2014, Blochliger 2015). Likewise, assessment caps that impose a tax cost on moving may shift construction from older built-up areas to cheaper undeveloped land.

However, sparse empirical research has examined how assessment caps directly affect residential construction. Hoyt et al. (2011), using an instrumental variable approach and controlling for state fixed effects, found that the presence of property tax limits directly increases home prices but found no evidence of an effect of assessment limits on the number of housing permits. This paper contributes to this literature by analyzing the relationship between assessment caps and residential construction at the county level and by exploring potential interaction effects among a county's assessment cap policy, property tax rate, and growth rate in median home value. This paper examines how property tax assessment caps affect the number of new home building permits using county-level panel data.

To investigate how homestead assessment caps, in combination with property tax rates and home value appreciation, influence home building, this paper employs a fixed-effects approach using panel data with counties across the United States from 2007 to 2017. Data on home building comes from the U.S. Census Bureau's Building Permits Survey. The paper constructs a longitudinal county-level homestead assessment cap dataset using data from the Lincoln Institute of Land Policy supplemented with historical state laws and local ordinances accessed through LexisNexis. The paper relies on Census and ACS data to construct county-level measures of property tax rate, home value appreciation rate, and additional economic and demographic controls.

With the full set of controls, results show that the presence of a homestead assessment cap has a negative association with the number of newly permitted housing units per 100,000 people in a county but becomes statistically significant when taking the inverse hyperbolic sine of newly permitted units per 100,000 people. However, the presence of an assessment cap explains relatively little variation both in the number of permitted new units and the inverse hyperbolic sine of new units. Moreover, the magnitude of the cap's negative association with the inverse hyperbolic sine of new units diminishes as the county's appreciation rate or property tax rate increases.

It is surprising that appreciation diminishes the cap’s negative association because the assessment cap is likely to be binding on a larger share of properties when the appreciation rate is higher. A higher appreciation rate for an individual property implies a larger reduction in taxable value below market value from the cap, raising the tax cost of any property change that would reset taxable value to market value. However, the current measure imperfectly captures the actual reduction in taxable value and likely proxies expected future appreciation. Expected future appreciation increases the expected tax benefit for housing in counties with the cap, which could increase demand for housing units in these counties and potentially explain this unexpected result.

Section 2 explains my methodological framework. Section 3 describes my data. Section 4 reports the results. Section 5 concludes.

2.2 Methods

The empirical specifications entail regressions of county-level residential construction variables from the Census Building Permits Survey on assessment cap and property tax policies for each year from 2007 through 2017. My controls are primarily from the Census ACS 5-year samples as county-level variables are not available for all counties in the 1-year samples.

For my initial state-level treatment regressions, I use the fixed effects model:

$$Y_{it} = \beta_0 A_{st} + \beta_1 L_{st} + \beta_2 T_{it} + \boldsymbol{X}_{it}\beta_3 + \alpha_i + \gamma_{dt} + u_{it} (1)$$

for county i, state s, Census division d, and year t. Y is the outcome variable: (1) the number of new privately-owned housing units for which building permits were issued per 100,000 people and (2) the inverse hyperbolic sine of the number of new privately-owned housing units issued building permits per 100,000 people. A is the assessment cap policy that is the key explanatory variable for each specification: (1) a dummy variable for the presence of a statewide homestead assessment cap and (2) a dummy variable for if a property's change in use, size, or zoning resets its taxable value under a statewide assessment cap to full market value. L is a dummy variable for if the state has local variation in the presence or rate of property tax assessment limits. L only ever equals one for Georgia, Hawaii, Illinois, Maryland, and New York. T is the property tax rate. $\boldsymbol{X}$ is a vector of controls: the county's total population, median household income, unemployment rate, share of the total population who is Black alone or Hispanic alone, share of the total population who is less than 18 years old, and share of the total population who is at least 65 years old. α_i and γ_{dt} are the county fixed effects and Census division-year effects, respectively.

For an alternative dependent variable, I take the inverse hyperbolic sine of new housing units per 100,000 people because the distribution of the number of new units per 100,000 people exhibits a skewed distribution from a binding lower bound at zero. Taking the inverse hyperbolic sine helps normalize the distribution except that the nearly 10% of observations with zero values remain at the zero-lower bound. Unfortunately, taking the inverse hyperbolic sine worsens the fit of the model.

For additional specifications, I drop *L* and instead add county-specific assessment cap policies in Hawaii, Illinois, Maryland, and New York to *A*. In 2009 and 2010, Georgia had a statewide assessment freeze. In all other years, I drop all Georgia counties because I lack data on which Georgia counties have assessment cap policies. As a baseline for these county-level treatment regressions, I use the fixed effects model:

$$Y_{it} = \beta_0 A_{it} + \beta_1 T_{it} + \boldsymbol{X}_{it}\beta_2 + \alpha_i + \gamma_{dt} + u_{it} (2)$$

for county *i*, Census division *d*, and year *t*. *A* is the homestead assessment cap policy that is the key explanatory variable for each specification: (1) a dummy variable for the presence of a homestead assessment cap, (2) a dummy variable for if a property's change in use, size, or zoning resets its taxable value to full market value, and (3) the maximum annual percentage increase allowed by the homestead assessment cap. Because county-level observations within a given state are closely related, I report my county-level treatment regressions using robust standard errors clustered at the state level.

For the full specifications, I use the following fixed effects model:

$$Y_{it} = \beta_0 A_{it} + \beta_1 T_{it} + \beta_2 G_{it-2} + \beta_3 A_{it} T_{it} + \beta_4 A_{it} G_{it-2} + \beta_5 T_{it} G_{it-2} + \beta_6 A_{it} T_{it} G_{it-2} + \beta_7 V_{it-2} + \boldsymbol{X}_{it}\beta_8 + \alpha_i + \gamma_{dt} + u_{it} (3)$$

where *G* is the percentage growth in a property's full market value, which I call the appreciation rate. $G_{it-2} = \frac{V_{it-2} - V_{it-3}}{V_{it-3}}$ where *V* is median home value. For the appreciation rate variable G_{it} and the median home value variable V_{it}, I use G_{it-2} and V_{it-2} because the ACS 5-year otherwise includes median home values from *t+1* and *t+2* periods. Arranging the plans, financing, and permitting for new housing units usually takes several months or years, so I expect lagging median home value and its percent change to more directly influence the number of new housing units permitted.[15] I assume only these lagged versions of median home value and percent change in median home value belong in the estimating equation for homebuilding. However, using percent change in lagged median home value requires excluding 2007, 2008, and 2009 from these regressions because the earliest ACS 5-year is 2005-2009, which is year 2007 in my regressions.[16] Note the lag does not address endogeneity concerns with this model (Bellemare et al. 2017, Reed 2015).

Using a fixed effects model with mean-differencing requires the assumption of strict exogeneity that the covariance between the variables in the model for any and every given year *t* and the error term in every year *t* is zero. Hoyt et al. (2011) finds that property tax limits like assessment caps contribute to home value appreciation. Appreciation is likely part of the error term because it reflects increased demand for new housing units. Hence, the assessment cap likely covaries with the error term in equations 1 and 2, violating the identification assumption of strict exogeneity.

Equation 3 includes an appreciation rate variable. However, appreciation rate likely correlates with homebuilding in prior years as well as time-varying land availability and land use and building restrictions that also influence homebuilding but are in equation 3's error term. Thus, equation 3 regressions also likely violate strict exogeneity. For strict exogeneity to hold, I

[15] Unlagged median home value level and percent change variables, however, may better capture omitted variables that influence homebuilding by shaping expectations about future appreciation.
[16] Keeping years 2007, 2008, and 2009 in the analysis with percent change in two-year lagged percent change in median home values would require imputing median home values for 2004, 2005, and 2006 from weighted averages of median home values in the 2000 Census and 2005-2009 ACS 5-year.

assume that land availability, regulation, and any other omitted variables affecting homebuilding and correlated with covariates in the regressions are unlikely to change significantly between 2010 and 2017 and hence largely captured by county fixed effects. For strict exogeneity to hold, I also assume that past homebuilding doesn't correlate with current homebuilding after controlling for equation 3's covariates, and therefore doesn't enter equation 3's error term.

Future work should explicitly address these identification challenges by including instrumental variables at least for median home value and percent change in median home value, which are likely affected by past homebuilding and omitted time-varying housing supply and demand factors. Future work could adopt a dynamic panel model or add other time-varying housing supply and demand factors directly into the model to reduce omitted variable bias. However, including past homebuilding and other endogenous regressors will also require instrumental variables and consideration of multicollinearity.

Because the number of housing units in prior years is correlated with u_{it}, coefficients may be biased if covariates in prior years are also correlated with u_{it} or past number of housing units belongs in the true model. The omission of other time-varying variables like land use regulation and local construction costs may also bias coefficients. The regressions likely also suffer some bias due to measurement error in the property tax rate and appreciation rate variables. The property tax rate, measured as property tax revenue divided by aggregate owner-occupied home value in the county, systematically omits from the denominator the value of rental and non-residential real property in the county. The appreciation rate relies on reported home values averaged across five years and assumes the percent change in the median owner-occupied home value is equivalent to the mean percent change in home value in the county.

2.3 Data

This paper uses county-level data from 2007 to 2017 across the United States. Table 1 summarizes the variables used in the county-level treatment regressions. The state-level treatment regressions include 32,144 observations, but the baseline version of the county-level regressions includes only 30,512 observations because of missing county-level data on assessment cap policies in Georgia. Including the appreciation rate variable shrinks the sample to the 22,103 observations from 2010 to 2017. The regressions analyzing the effect of the assessment cap rate exclude observations with no assessment cap, which further shrinks the sample size to 5,266 for two regressions.

2.3.1 Dependent Variables

This paper's dependent variables are county-level measures of new housing units constructed from 2007 to 2017 created from Census Building Permits Survey annual data on the number of new housing units for which building permits were issued in each county and ACS 5-year data on county population. The dependent variable in columns 1 and 2 of Table 2 and in Table 3 is the number of new privately-owned housing units issued building permits per 100,000 people. However, this variable faces a strict zero lower bound. Consequently, it exhibits a highly skewed distribution, with nearly 10% of observations equaling zero. The dependent variable in columns 3 and 4 of Table 2 and in Table 4 is the inverse hyperbolic sine of new housing units per 100,000 people. Coefficients reported in Table 2 columns 3 and 4 and Table 4 translate to a percentage change in the number of permitted units per 100,000 people. Taking the inverse hyperbolic sine normalizes the distribution of positive values. However, the large cluster of zero values remains, and the inverse hyperbolic sine is sensitive to scale (Aihounton and Henningsen 2021).

2.3.2 Key Explanatory Variables

The primary explanatory variable of interest is the presence of a homestead assessment cap. This paper constructs a county-level dataset with a separate dummy variable for the presence of a homestead assessment cap applying to state, county, municipal, school district, and special district property taxes. I do not count homestead assessment caps that condition eligibility on personal characteristics unconnected to property like income, age, disability, or veteran status. The data come from the Lincoln Institute of Land Policy and searching historical state laws and local ordinances in LexisNexis. These dummy variables combine into a single county-level cap dummy variable for the presence of a homestead assessment cap in the county at any level of government.[17]

In additional specifications, the primary explanatory variable of interest is the presence of a homestead assessment cap that resets taxable value to market value when property changes use, size, or zoning. In others, the homestead assessment cap rate is the primary explanatory variable of interest. It is the maximum allowable annual percent increase in taxable value of an owner-occupied home. These also originate from Lincoln Institute of Land Policy data and LexisNexis. Cap rate is weighted by property tax revenues at each government level. The expected effects of these assessment cap variables are ambiguous because they both encourage home construction by insuring against the tax-price risk of homeownership and discourage home construction by creating a tax cost to changes in the property associated with construction.

Additional explanatory variables of interest are the property tax rate, the appreciation rate, median home value, the interaction between property tax rate and appreciation rate, the

[17] An alternative approach to account for how much of the property tax in the county is subject to the cap would combine the dummy variables for a cap at each level of government weighted by property tax revenues at each level of government, using data from the Census State and Local Government Finance Survey.

interaction between cap policy and property tax rate, the interaction between cap policy and appreciation rate, and the interaction between cap policy, property tax rate, and appreciation rate. The paper proxies property tax rate with aggregate property tax revenues as a percent of aggregate owner-occupied home value in the county, using data from the Census State and Local Government Finance Survey and the ACS 5-year. State property tax revenues and New York City's revenues are apportioned to counties by population. Property tax revenues for all other jurisdictions are apportioned entirely to the primary county they overlap. The property tax rate directly increases the cost of improving property value, and hence is expected to reduce the number of new housing units.

The paper proxies home value appreciation rate with the growth rate in the median home value using the ACS 5-year, lagged by two years. The appreciation rate, reflecting rising demand for homes in the county, is expected to increase home construction. Median home value, reflecting the high demand for homes in the county, is likewise expected to increase home construction.

The expected effect of the interaction of an assessment cap (with a reset trigger) and property tax rate is ambiguous. The cap's tax cost to construction-related changes in property is increasing in the property tax rate. However, the assessment cap's value as insurance against property tax increases also is increasing in the property tax rate. I expect the interaction of the assessment cap and the appreciation rate to reduce home building because the cap's tax cost of construction-related changes in property is also increasing in the appreciation rate. However, higher recent appreciation may upwardly revise expectations of future home value growth, which raises the expected after-tax value of new construction more in the presence of an assessment cap. I expect the interaction of property tax rate and appreciation rate to increase home construction because of the combination of increased risk of tax-induced displacement and increased value of building new housing units. I expect the interaction of all three variables: assessment cap, property tax rate, and appreciation rate to reduce home construction because it reflects tax cost of construction-related property changes that reset taxable value, which is increasing in both the property tax rate and the appreciation rate.

2.3.3 Control Variables

From the 2009-2019 ACS 5-year at the county level, I obtain the following county-level control variables for 2007-2017: county population, county median household income, county unemployment rate, the share of total county population who is Black only or Hispanic only, the share of county population younger than age 18, the share of the county population age 65 or older, Census Division-year effects, and county fixed effects.

2.4 Results

2.4.1 State-Level Treatment

Table 2 presents county fixed effects estimates of how assessment cap policies affect the number of newly permitted housing units per 100,000 people (columns 1 and 2) and its inverse hyperbolic sine (columns 3 and 4). The number of newly permitted housing units per 100,000 people ranges from zero to 15,787. Standard errors are clustered at the county level.

Table 2 shows a statistically significant and positive effect of being in a state with local variation in homestead assessment caps on the number of newly permitted housing units per 100,000 people but no significant effect of statewide assessment caps. Columns 1 and 2 show that the presence of homestead assessment caps that vary across localities within the state is associated with an increase in permitted housing units per 100,000 people of 37 (0.12 standard deviations). Columns 3 and 4 imply that being in a state with local variation in assessment caps increases home building by 21%. This suggests that in local option states, the cap's role as insurance against tax-price risk that preferences housing investment more than offsets any reduction in new housing units from the cap's lock-in effect. Local option states may impose caps based on the relative welfare costs of tax-price risk and the lock-in effect specific to each county such that the average effect on homebuilding is more positive. However, home price appreciation may drive both the adoption of local assessment cap policies and homebuilding. Even if there is a causal relationship, a standard deviation increase in population or median household income is associated with larger increases in the number of new housing units. Results in Table 2 imply the magnitude of the local option's effect is comparable to raising median household income by \$4,000-\$7,000 or population by 37,000-42,000.

2.4.2 County-Level Treatment

Table 3 presents results of county fixed effects estimates of how assessment cap policies affect the number of new housing units issued building permits per 100,000 people with standard errors clustered at the state level. In column 1, before controlling for appreciation rate, presence of a homestead assessment cap has a positive and statistically significant association with new housing units per capita. Adopting a homestead assessment cap policy is associated with an increase in the number of new housing units per 100,000 people by 43 (0.14 standard deviations). This is comparable to the increase expected from increasing median household income by \$4,500 or population by 45,000 people. There is no evidence an effect of the homestead assessment cap rate. After controlling for appreciation rate, the coefficient for assessment cap changes sign and loses statistical significance. Appreciation rate may be capturing the tax-price risk insurance and housing tax reduction channel to the extent these are capitalized into home value.

The appreciation rate has a positive and statistically significant association with homebuilding before including interaction terms. An extra 1% appreciation is associated with an extra four new housing units per 100,000 people. Median home value has a negative and statistically significant association with homebuilding in column 6. A $100,000 rise in median home value is associated with 157 fewer new units per 100,000 people. This may reflect the housing stock having already largely adjusted to housing demand reflected in past home value after controlling for recent home price appreciation. In columns 2-6 and 8, property tax has a negative and statistically significant association with homebuilding. In columns 2-6, a one percentage point increase in the property tax rate is associated with a two fewer new units per 100,000 people. This is consistent with real property tax being partly a tax on the value of buildings on the land. None of the interaction terms are statistically significant.

Table 4 presents results of county fixed effects estimates of how assessment cap policies affect the inverse hyperbolic sine of the number of new housing units permitted per 100,000 people with standard errors clustered at the state level. Contrary to the results in Table 3 column 1, results in Table 4 columns 2-6 show a statistically significant and negative effect of the homestead assessment cap after controlling for appreciation. The presence of an assessment cap is associated with a decrease of 0.30-0.36 standard deviations in the inverse hyperbolic sine of the newly permitted housing units per 100,000. Adding an assessment cap is associated with a 43-49% decrease in newly permitted housing units per 100,000. This is comparable to the effect of raising median household income by $24,000-$31,000 or population by 134,000-154,000 people. The difference between the presence of an assessment cap and an assessment cap with a use, size, or zoning change reset trigger appears negligible. There is no evidence of an effect of the cap rate.

The property tax rate in the absence of a homestead assessment cap and appreciation has no significant association with the number of newly permitted housing units per 100,000. In the presence of a homestead assessment cap, the property tax rate has a statistically significant but economically insignificant positive association with the number of permitted units. The appreciation rate has a statistically significant but minuscule positive association with the number of permitted units. An extra 1% appreciation in median home value, absent a property tax, is associated with a 0.8-1.3% increase in the number of permitted units per 100,000 people.

Notably, all the interactions in columns 4 and 6 are statistically significant, except one that is marginally significant. The double interaction terms have small positive coefficients, and the triple interaction term has a small negative coefficient. Adding an assessment cap is associated with a 49% decrease in permitted new housing units if there is no appreciation and no property tax. It is associated with a 45% decrease with no appreciation and a mean property tax rate (2.5%), a 44% decrease with a mean appreciation rate (1.6%) and a mean property tax rate, a 41% decrease with an appreciation rate of 10% (1.9 standard deviations over the mean) and a mean property tax rate, and a 28% decrease with a 10% appreciation rate and 10% property tax rate (1.6 standard deviations over the mean).

This suggests that under normal property tax rates and appreciation rates the cap's effective tax on property changes creates a lock-in effect that reduces new homebuilding by more than the cap's role as a tax preference and tax-price insurance for housing increases homebuilding. The results in Table 4 further indicate that the cap's housing tax preference and tax-price insurance effects are more strongly increasing in both property tax rate and appreciation rate than the lock-in effect is. However, the cap's lock-in effect appears to grow more when property tax rate and appreciation rate increase together, whereas the cap's housing tax preference and insurance effects appear to grow more with either property tax rate or appreciation rate increasing independent of one another.

A 1 percentage point increase in the appreciation rate is associated with an increase in the number of permitted housing units by 0.7% in the absence of property taxes, by 0.9% with a mean property tax rate and no assessment cap, by 1.5% with a mean property tax rate and an assessment cap, and by 1.4% with a 12% tax rate (2 standard deviations over mean) and an assessment cap. Without an assessment cap or appreciation, the property tax rate has no statistically significant association with the number of permitted units. With an assessment cap, a percentage point increase in the property tax rate is associated with an increase in permitted new units of 2.7% with no appreciation and 2.6% with a 10% appreciation rate.

Median home value has a statistically significant negative association with the number of permitted units in all specifications except those with the assessment cap rate (columns 8 and 9). An extra $100,000 in median home value is associated with a 40% fall in the number of new units per 100,000. Population and median household income have positive and statistically significant associations with permitted new units across all specifications. The unemployment rate has a negative and statistically significant association with the number of new units only in column 1, which omits the appreciation rate.

2.5 Conclusion

Property tax assessment caps slow the relative growth in tax burden for owners of rapidly appreciating property (Augustine et al. 2009, Haveman and Sexton 2008, Twait 2011). These caps can result in massive gaps between a property's taxable and market value that create an incentive to avoid actions that would reset the property's taxable value to market value. To the extent that actions triggering a reset to market value are associated with residential construction, assessment caps will reduce the likelihood of construction on highly appreciated property. However, assessment caps may also increase the relative demand for long-term homeownership in jurisdictions with caps by insuring against a property's future growth in taxable value. Furthermore, caps on only residential taxable value growth create an incentive to convert non-residential property to residential. Thus, the overall effect of assessment caps on residential construction is ambiguous.

The analysis employs a panel dataset of counties across the United States between 2007 and 2017. The results are inconclusive. Before controlling for appreciation, results show homestead assessment caps have a positive association with homebuilding. With the full set of controls, results show that homestead assessment caps have an overall negative association with residential construction. However, the positive association is only statistically significant in the level regression in Table 3 column 1. By contrast, the negative association is only statistically significant in Table 4 regressions that use the inverse hyperbolic sine of the number of new units per 100,000. Moreover, the magnitude of the negative effect of assessment caps on homebuilding in Table 4 is decreasing in both home appreciation and property tax rates. The results suggest the cap's role as tax-price insurance and a housing tax cut may increase housing at a more constant quantity of units per capita, whereas the cap's lock-in effect may deter construction of new units at a more constant rate. Future work is needed to resolve these inconclusive findings.

This paper ignores the likely autocorrelation with the current year's number of permitted housing units being a function of past years and ignores spatial correlation among nearby counties. Future research could address autocorrelation with a dynamic panel model. This paper also ignores the potential endogeneity of housing price appreciation, influenced by past home building trends. Future research could include instrumental variables for home price appreciation.

Future work could examine additional dependent variables like the value of new construction, number of housing units, and vacancy rate. Rather than simple interaction variables, future work could estimate the effective size of the assessment cap tax break using data on past appreciation and past and current cap rates multiplied by the current tax rate. It might also help to control for other policies expected to affect construction. Ideally, an analysis would be parcel-level, estimating the likelihood of construction on a given parcel based on the effective assessment cap tax break, time-varying controls, and parcel fixed effects.

The result in Table 4 columns 4 and 6 that the appreciation rate and property tax rate diminish the magnitude of the cap's effect on homebuilding is surprising. A possible explanation is that the appreciation rate may proxy for expected future home price growth. As expected, future home price growth increases, the cap becomes more valuable as insurance against taxable value growth. Likewise, expected future appreciation in property values increases the expected tax advantage of converting property from a use that is not subject to an assessment cap to one that is.

Additionally, recent growth in a county's median home value may only weakly reflect the actual gap between taxable value and market value the cap creates on individual properties within the county. It would be useful to study the effect of the cap using data on the actual gap between market and taxable value the cap creates. Future research could also examine how the cap may change the distribution of housing within a county.

The property tax rate may diminish the magnitude of the cap's effect because it reflects the flexibility of taxing jurisdictions to interchange tax rates and assessment value. In this case, the assessment cap has little expected effect on countywide tax burden in the absence of tax rate limits. Another possible explanation is that a higher property tax rate increases the advantage of converting non-residential property to housing as many states exclude non-residential property from the assessment cap.

Furthermore, this paper's property tax rate measure is a county's aggregate property tax revenues as a percent of aggregate owner-occupied home value. Hence, higher values of this variable reflect higher property tax rates and a higher aggregate value of non-homestead property relative to homestead property. Counties with relatively little of their current property value in homesteads may exhibit a more elastic supply of homesteads, either due to more substitutable non-homestead properties or sufficient property wealth in the county to accommodate more housing. Additionally, the more a jurisdiction relies on non-homestead property tax revenues, the less likely the tax benefit of the homestead assessment cap will be offset by higher tax rates. Future research could examine how assessment caps affect the composition of property types (homestead, non-homestead residential, non-residential developed, and undeveloped).

Overall, this paper finds the observed relationship between assessment caps and home construction is sensitive to the specification selected. Results suggests a positive relationship in levels between assessment caps and homebuilding when not controlling for appreciation. When taking the inverse hyperbolic sine of the dependent variable and controlling for appreciation, results indicate that adopting assessment caps may have modest adverse consequences for home construction, another avenue by which assessment caps may burden prospective new homebuyers while providing relief for existing homeowners. Jurisdictions with homestead assessment caps may wish to consider alternative means of helping cash-poor homeowners keep their homes. For example, instead of capping assessment increases, a jurisdiction could cap homestead property tax bills as a percent of household income. Another option is requiring taxing jurisdictions to publicly disclose and approve any property tax rate that would increase property tax revenue, which Cornia and Walters (2006) found to reduce tax increases from home value appreciation. Nevertheless, more research is required to estimate the welfare tradeoffs of these property tax relief alternatives.

APPENDIX A

A.1 Aspatial Segregation Measures in Rothwell and Massey (2010)

The dissimilarity index, a popular evenness measure, compares a group's population share in each sub-area unit to that in the MSA overall. Rothwell and Massey (2010) construct a Dissimilarity Index of Poverty and another evenness measure, a population-weighted Neighborhood Gini Index of inequality in median household income across sub-areas.

Exposure reflects the degree to which different groups reside in common areas. Rothwell and Massey (2010)'s exposure index measures the ratio of the likelihood a randomly-selected person in an MSA belongs to a different population group than that of another person randomly selected from their sub-area to the share of the randomly selected person's population group in an MSA.

A.2 Construction of Aspatial Information Theory Index Measures of Segregation

To construct aspatial segregation measures, I merge ACS 2016 5-year block-group level data with the 2016 block group to 2000 MSA crosswalk. Then I create variables for number of block groups in each MSA, total population in each MSA, MSA population below poverty, total number of households in each MSA, total number of households with income below $25,000 in each MSA, mean block-group-level median household income in each MSA, rank of a block group's median household income within each MSA, and an MSA identifier variable. Next, I construct the following MSA-level information theory index measures of segregation:

Ordinal Information Theory Index (Theil's *H*) for Poverty: I use the Stata "rankseg" command to create an ordinal information theory index using population counts of bins for the following percentage ranges of the poverty threshold: 0-49%, 50-99%, 100-124%, 125-149%, 150-184%, 185-199%, and 200%+. I set order at zero.

Ordinal Information Theory Index for Income: I use the Stata "rankseg" command to create an ordinal information theory index using number of household counts of bins for the following household income ranges: $0-9,999, $10,000-14,999, $15,000-19,999, $20,000-24,999, $25,000-29,999, $30,000-34,999, $35,000-39,999, $40,000-44,999, $45,000-49,999, $50,000-59,999, $60,000-74,999, $75,000-99,999, $100,000-124,999, $125,000-149,999, $150,000-199,999, and $200,000+. I set order at zero.

Information Theory Indexes for Race: For the simpler non-ordinal information theory indexes, I create a "Theil's *H*" index variable *H*, using the Reardon and Townsend (2018)'s Stata "seg" command. The MSA-level indexes reflect the following equation (equation 3) from Reardon (2011) and Reardon, Bischoff, Owens, and Townsend (2018):

$$H = 1 - \frac{\sum_{j=1}^{J} \frac{P_j}{P} E_j}{E} \quad (3)$$

where

$$E = \begin{cases} \sum_{m=1}^{2} \frac{P_m}{\sum_{n=1}^{2} P_n} \ln \frac{\sum_{n=1}^{2} P_n}{P_m} \text{ if } 0 < \frac{P_m}{\sum_{n=1}^{2} P_n} < 1 \\ 0 \text{ otherwise} \end{cases} \quad (1)$$

and

$$E_j = \begin{cases} \sum_{m=1}^{2} \frac{P_{jm}}{\sum_{n=1}^{2} P_{jn}} \ln \frac{\sum_{n=1}^{2} P_{jn}}{P_{jm}} \; if \; 0 < \frac{P_{jm}}{\sum_{n=1}^{2} P_{jn}} < 1 \\ 0 \; otherwise \end{cases} \quad (2)$$

for block group *j*, population *P*, and two racial categories *m*. I calculate the White-Black race-pair index. White is the White non-Hispanic population. Black is the Black non-Hispanic population.

A.3 Construction of Spatial Information Theory Index Measures of Segregation

After creating MSA-level aspatial segregation measures, I add the MSA identifier variable to a datafile from the NBER Census Block Group Distance Database and divide the NBER block group distance datafile into separate files by MSA. The NBER datafile includes the distance in miles between every pair of 2010 block groups within 50 miles of one another. NBER calculates great-circle distances using the Haversine formula from internal points in the block group (point closest to a block group's geographic center that is within the boundaries of the block group). I add all the block-group-level population count variables to each file twice (one corresponding to block group one and the other corresponding to block group two) so that each block group pair has their individual block group population counts for each poverty and income category. Next, I create the following distance-based segregation measures (but only report regressions using information theory indexes):

Spatial Ordinal Information Theory Indexes for Poverty and for Income: Following Reardon et al. (2006), I create separate indexes that account for the population composition of nearby block groups up to each of the following radii *r*: 500m, 1000m, 2000m, and 4000m. The "rankseg" command doesn't include a spatial option, so I create spatial-adjusted ordinal bins. First, I create the biweight proximity function (equation 5):

$$w_{jk} = \begin{cases} \left[1 - \left(\frac{d_{jk}}{r}\right)^2\right]^2 & if\ d_{jk} < r \\ 0\ otherwise & \end{cases} \quad (4)$$

for every combination of block groups j and k. For each income group m in each block group j, I create the spatially weighted local population composition (LPC) function (equation 6):

$$LPC_{jm} = \frac{\sum_{k\in J} P_{km} \times w_{jk}}{\sum_{k\in J}(\sum_{n=1}^{2} P_{kn}) \times w_{jk}} (5)$$

that divides the sum of all these weighted nearby-block-group populations in group m by the sum of weighted nearby-block-group populations overall. I weight each aspatial population count bin by LPC_{jm} to create spatial-adjusted ordinal bins and run "rankseg" command by MSA with order zero to create MSA-level spatial ordinal information theory indexes.

Spatial Information Theory Indexes for Race: Following the procedure for the spatial information theory index in equation 8, I calculate spatial versions of the Black-White information theory measures of racial segregation above using the spatially weighted LPC function to weight the aspatial racial population counts in the information theory equation.

A.4 Construction of Control Variables

MSA-Level US Census 2000 Control Variables: From the decennial US Census 2000 SF1 and SF3 data files at the MSA level, I obtain the following MSA-level control variables: the natural log of total MSA population in 2000, share of the total MSA population who is Black only or Hispanic only, share of total MSA households with annual household income less than \$20,000, and share of total MSA households with annual household income at least \$60,000.

MSA-Level ACS 2016 5-year Gini Index of Income Inequality: The Gini measure of MSA income inequality comes from ACS 5-year 2016 MSA-level data. I use the Missouri Census Data Center's Geocorr program to crosswalk CBSA-level Gini Index of Inequality from ACS 2016 5-year to year 2000 MSAs and PMSAs using population-based weights.

MSA-Level Number of Municipal Jurisdictions in 2002: Jurisdictional fragmentation likely increases income segregation. Fragmenting municipal services within an MSA increases the incentive for high-income people to self-sort into more expensive neighborhoods by exacerbating neighborhood quality differences. It also will encourage high-income municipalities to restrict housing available for lower income families to avoid free riding and to capture rent from local housing demand. From the 2002 Census of Governments (COG) list of local governments, I create a count variable for the number of municipalities (cities, townships, etc.), which excludes county and all non-general-purpose governments. Joint city/county governments like San Francisco count only once. Separate county governments don't count at all. This definition tries to follow Rothwell and Massey (2009, 2010) and Lens and Monkonnen (2016). But I multiply the number of municipalities by the number of general-purpose governments. The 2002 COG file identifies a municipality's county but not MSA, so I use the Missouri Census Data Center's Geocorr program to match year-2000 counties to year-2000 MSAs and PMSAs.

A.5 IV Construction

MSA-Level 1982 Local Public Protective Inspection and Regulation Expenditures as a Share of Total Local Public Revenues: Saiz (2010) uses this variable to instrument for WRLURI in its regressions on housing supply elasticity. I adopt it for my segregation regressions under the assumption that protective inspection and regulation spending only affects segregation through land use regulation. To create the protective inspection and regulation variable, I use 1982 Census State and Local Government Finance Data at the individual jurisdiction level and crosswalk these year-1982 jurisdictions into year-2000 MSAs.[18]

[18] 1982 Census State and Local Government Finance Data at the individual jurisdiction level comes from https://www.census.gov/programs-surveys/gov-finances/data/historical-data.html. I crosswalk changes in geographic

After merging 1982 state and local government finance data with the crosswalk, I collapse the dataset by 2000 MSA. This creates variables for total protective inspection and regulation expenditures and total revenues of all local governments in 1982 within the 2000 MSA counties, using county to MSA land area weights. Dividing MSA-level total protective expenditures by MSA-level total revenues produces a protective expenditure share variable. The 2SLS regressions use log of protective expenditure share as an instrumental variable.

MSA-Level Number of Streams Instrumental Variable: Following Dawkins (2005), I join the 1991 USGS 48-state hydrography layer from 1:2,000,000-scale DLG data to NHGIS 2000 MSA boundary data in ArcGIS Pro. I export the attribute table identifying the list of stream segments in each MSA to a CSV file and import the data to Stata. For each MSA, I count the number of stream segments at least 1km in length. I also calculate the total length of all stream segments within each MSA but currently only use the stream count variable.

A.6 Combining Data from Different Years and Geographic Units

2016 Block Group to 2000 MSA Crosswalk: Missouri Census Data Center matches every 2000 Census block to its corresponding 2000 Census PMSA or MSA. NHGIS crosswalks 2000 Census blocks to 2010 Census blocks.

ACS 2016 5-Year Block-Group-Level Data File: I create a single data file with ACS 2016 5-year block-group level data from all 50 states and DC, including geographic, population,

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GOVS ID over time and convert from 1982 GOVS ID to 2002 FIPS county code using Census of Governments files: (IDxWalk.txt and GOVS_to_FIPS_Codes_State_&_County_2007.xls). I adjust 2002 FIPS county codes for certain governments using David Dorn's list of changes since 1982 to reflect county boundaries in 2000 (https://www.ddorn.net/data/FIPS_County_Code_Changes.pdf). Otherwise, I assume county boundaries are unchanged between 1982 and 2002. Missouri Census Data Center provides a 2000 county to 2000 PMSA and 2000 MSACMSA crosswalk with land area weights (http://mcdc.missouri.edu/applications/geocorr.html). This paper defines 2000 MSAs as all 2000 PMSAs and MSAs (CMSAs are combinations of PMSAs and are thus ignored).

housing, income, and race variables. I merge ACS 2016 5-year block-group level data with the 2016 block group to 2000 MSA crosswalk. Block-group-level median household income is top coded at $250,000 and usually bottom coded at $2,500. I assume all block groups with median household income $250,000 or greater equal $250,000 and with $2,500 or less equal $2,500. For block groups with alternative bottom coding, I similarly assume the median household income equals the bottom code.

A.7 Preparing Regressions

I combine all these variables into a single data file and regress various measures of segregation on the WRLURI and its components, using ln(2000 population), 2016 Gini, share of households with income below $20,000 in 2000, share of households with income $60,000 or more in 2000, share of population in 2000 who is Black only or Hispanic only, and number of municipal jurisdictions in 2002. To instrument for the land use regulation variables, I use number of streams from the 1991 USGS hydrography layer and 1982 local public protective inspection and regulation expenditures as a share of total local public revenues.

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Figure 1.1

% of households with annual income >$100,000 by Census block group (2012-2016 ACS 5yr)

2000 Miami MSA

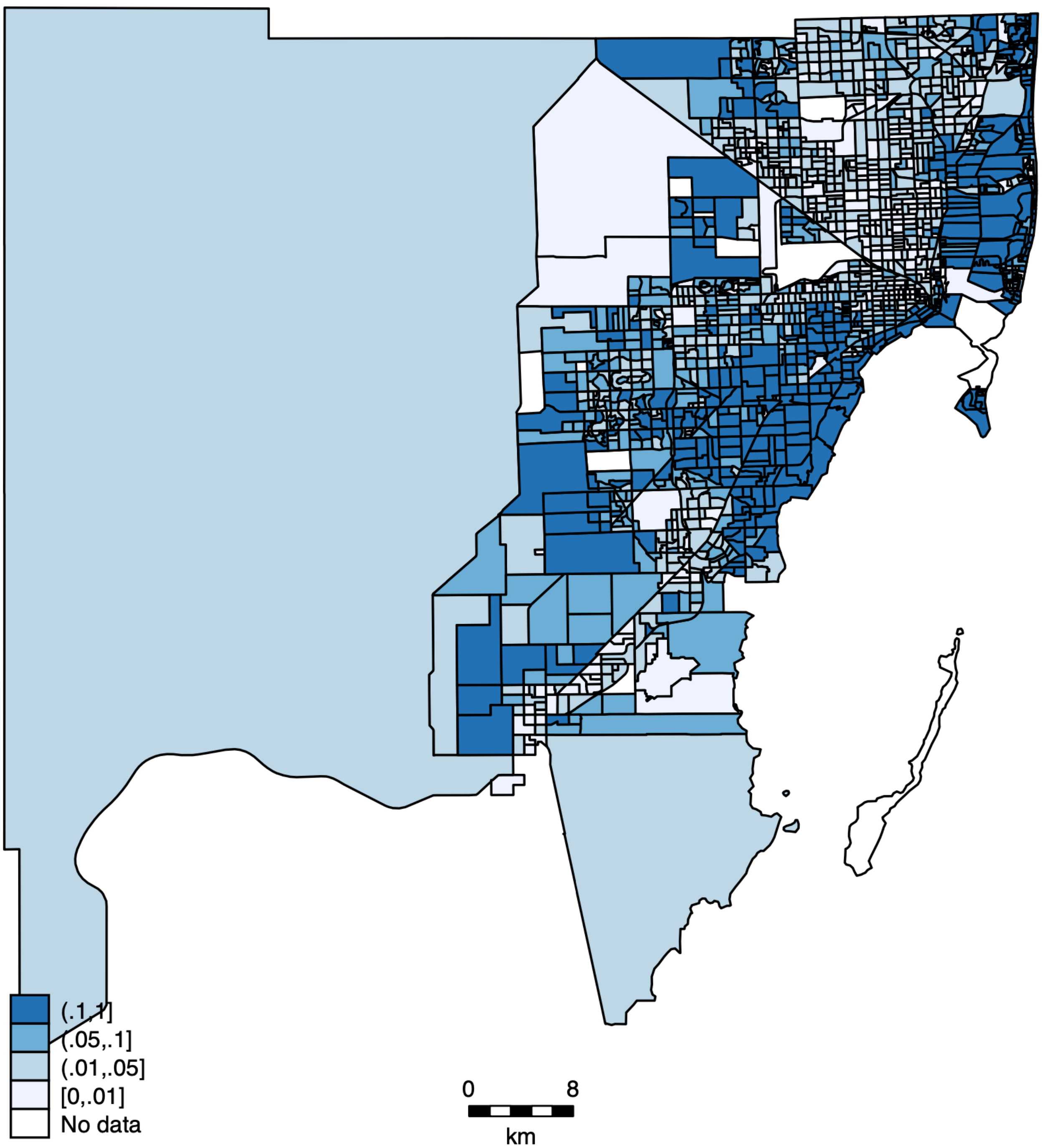

Figure 1.2

% of households with annual income >$100,000 by Census block group (2012-2016 ACS 5yr)

2000 Nashville MSA

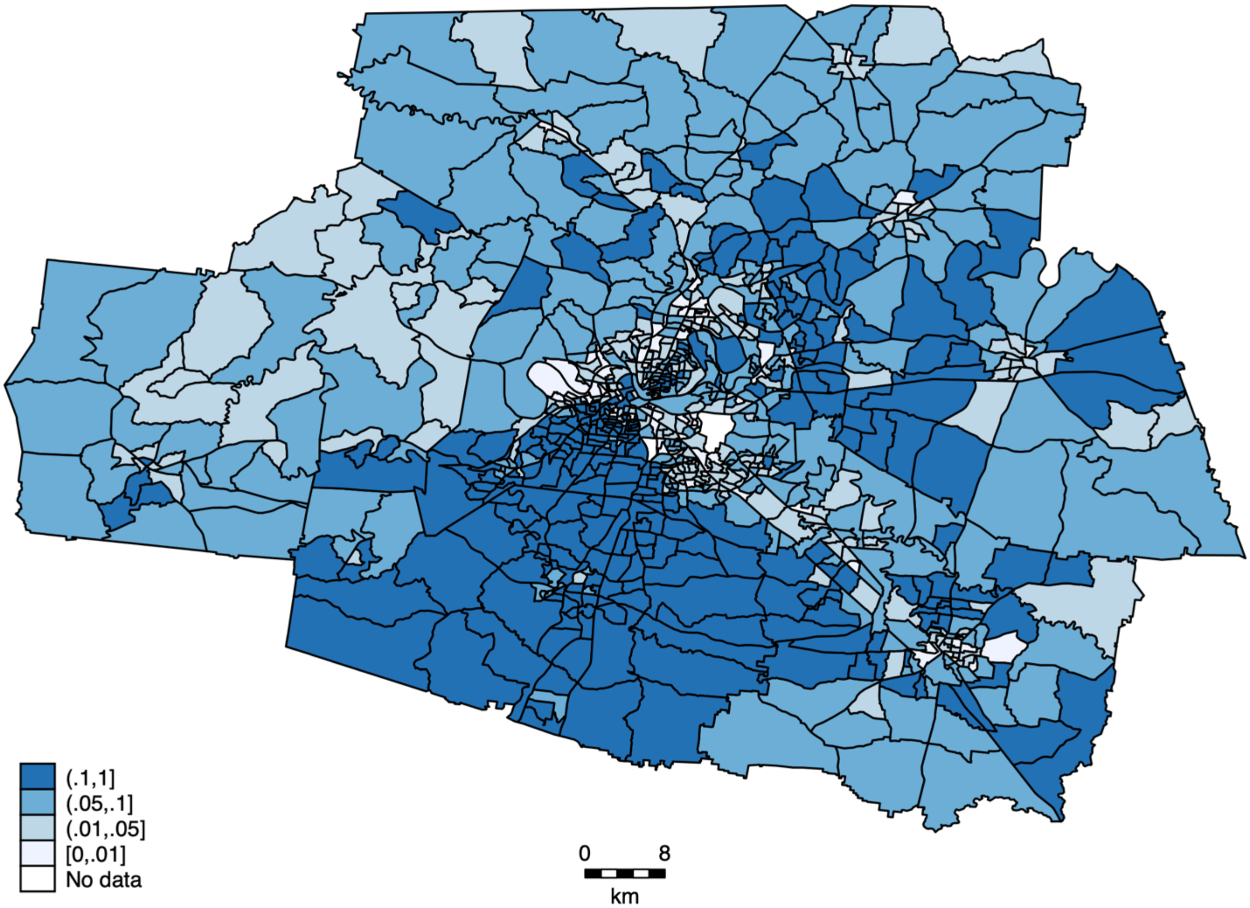

Table 1.1 Segregation Measure Correlations

	Information Theory Index of Household Income						Information Theory Index of Poverty Ratio						Black-White Information Theory Index					
Spatial Scale	**Aspatial**	**500m**	**1000m**	**2000m**	**4000m**	**8000m**	**Aspatial**	**500m**	**1000m**	**2000m**	**4000m**	**8000m**	**Aspatial**	**500m**	**1000m**	**2000m**	**4000m**	**8000m**
Information Theory Index of Household Income																		
Aspatial	1.00																	
500m	0.98	1.00																
1000m	0.93	0.97	1.00															
2000m	0.85	0.90	0.97	1.00														
4000m	0.80	0.85	0.92	0.97	1.00													
8000m	0.76	0.79	0.84	0.88	0.95	1.00												
Information Theory Index of Poverty Ratio																		
Aspatial	0.86	0.87	0.82	0.77	0.72	0.64	1.00											
500m	0.81	0.86	0.83	0.79	0.74	0.65	0.98	1.00										
1000m	0.75	0.81	0.85	0.84	0.79	0.68	0.93	0.97	1.00									
2000m	0.69	0.75	0.81	0.85	0.82	0.71	0.87	0.92	0.98	1.00								
4000m	0.68	0.74	0.80	0.85	0.87	0.80	0.84	0.88	0.93	0.97	1.00							
8000m	0.69	0.73	0.77	0.81	0.87	0.89	0.77	0.80	0.83	0.86	0.94	1.00						
Black-White Information Theory Index																		
Aspatial	0.31	0.27	0.23	0.22	0.26	0.33	0.32	0.28	0.23	0.23	0.29	0.37	1.00					
500m	0.30	0.27	0.24	0.23	0.27	0.34	0.31	0.28	0.24	0.25	0.30	0.39	1.00	1.00				
1000m	0.26	0.24	0.24	0.26	0.30	0.36	0.27	0.25	0.24	0.26	0.32	0.39	0.97	0.99	1.00			
2000m	0.24	0.23	0.24	0.28	0.33	0.39	0.25	0.24	0.25	0.29	0.35	0.42	0.94	0.96	0.99	1.00		
4000m	0.26	0.25	0.26	0.31	0.37	0.44	0.27	0.25	0.26	0.31	0.38	0.46	0.91	0.92	0.96	0.99	1.00	
8000m	0.30	0.29	0.30	0.34	0.41	0.49	0.28	0.27	0.29	0.33	0.41	0.51	0.85	0.87	0.90	0.94	0.97	1.00

Notes: Correlation Table of Information Theory Indexes in 295 metropolitan areas used in specifications with largest number of observations

Table 1.2 Information Theory Index of Household Income: Wharton Residential Land Use Regulation Index (WRLURI)

	Aspatial		500m radius		1000m radius		2000m radius		4000m radius		8000m radius	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
WRLURI	-0.004*	-0.010*	-0.004*	-0.012**	-0.004**	-0.014***	-0.005***	-0.016***	-0.005***	-0.017***	-0.004***	-0.014***
	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.004)	(0.001)	(0.004)	(0.001)	(0.003)
Log population	0.007***	0.007***	0.006***	0.006***	0.004**	0.004**	0.003*	0.003*	0.004***	0.003**	0.005***	0.005***
	(0.002)	(0.0017)	(0.0017)	(0.0017)	(0.0016)	(0.0017)	(0.0014)	(0.0015)	(0.0012)	(0.0014)	(0.0010)	(0.0011)
Gini	0.122	0.108	0.103	0.077	0.143*	0.104	0.125	0.074	0.082	0.034	0.059	0.025
	(0.091)	(0.0963)	(0.0894)	(0.0955)	(0.0845)	(0.0919)	(0.0759)	(0.0846)	(0.0645)	(0.0738)	(0.0487)	(0.0571)
% with household income	0.121	0.140	0.109	0.138	0.056	0.093	0.066	0.111	0.041	0.085	-0.006	0.026
<$20k	(0.088)	(0.092)	(0.088)	(0.093)	(0.084)	(0.090)	(0.075)	(0.082)	(0.061)	(0.070)	(0.044)	(0.052)
% with household income	0.159***	0.201***	0.143**	0.200***	0.090	0.160**	0.082	0.168**	0.059	0.148**	0.022	0.090**
>$60k	(0.061)	(0.073)	(0.061)	(0.073)	(0.060)	(0.071)	(0.055)	(0.066)	(0.046)	(0.058)	(0.034)	(0.045)
% Black or Hispanic	0.023*	0.024*	0.018	0.018	0.015	0.016	0.011	0.013	0.013	0.015	0.015*	0.017**
	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.011)	(0.012)	(0.010)	(0.011)	(0.008)	(0.008)
Number of municipalities	-1.664	-1.055	-0.821	-0.109	-0.129	-0.364	-0.645	0.268	-0.118	0.887	-0.398	0.447
(1000s)	(1.329)	(1.401)	(1.398)	(1.486)	(1.379)	(1.492)	(1.254)	(1.436)	(1.120)	(1.316)	(0.798)	(0.940)
Constant	-0.101***	-0.113***	-0.071*	-0.084**	-0.047	-0.060	-0.048	-0.062*	-0.053*	-0.068**	-0.064***	-0.077***
	(0.037)	(0.038)	(0.039)	(0.040)	(0.036)	(0.038)	(0.032)	(0.035)	(0.028)	(0.032)	(0.021)	(0.024)
Observations	293	291	293	291	293	291	293	291	293	291	293	291
Adjusted R^2	0.280	0.250	0.212	0.159	0.146	0.060	0.119	-0.038	0.133	-0.082	0.220	0.018
Underidentification p-value		0.000		0.000		0.000		0.000		0.000		0.000
Weak identification F-stat		18.693		18.693		18.693		18.693		18.693		18.693
Hansen J p-value		0.468		0.341		0.768		0.705		0.621		0.868

Notes: Unit of observation is MSA/PMSA with year 2000 boundaries. Dependent variable ranges from zero if no segregation to one if completely segregated. IVs are share of protective inspection expenditures and number of streams. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.3 Information Theory Index of Poverty Threshold Ratio: Wharton Residential Land Use Regulation Index (WRLURI)

	Aspatial		500m radius		1000m radius		2000m radius		4000m radius		8000m radius	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
WRLURI	-0.004	-0.006	-0.004	-0.008	-0.005*	-0.010*	-0.004**	-0.013**	-0.005**	-0.014***	-0.004***	-0.011**
	(0.003)	(0.006)	(0.003)	(0.006)	(0.002)	(0.006)	(0.002)	(0.005)	(0.002)	(0.005)	(0.001)	(0.005)
Log population	0.003	0.003	0.002	0.002	0.000	0.000	-0.000	-0.000	0.002	0.002	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Gini	0.162	0.148	0.143	0.113	0.203*	0.151	0.194*	0.126	0.144	0.082	0.103	0.064
	(0.114)	(0.117)	(0.113)	(0.116)	(0.109)	(0.112)	(0.104)	(0.108)	(0.088)	(0.094)	(0.070)	(0.078)
% with household income	0.218**	0.232**	0.198**	0.223**	0.128	0.166*	0.128	0.178*	0.068	0.115	-0.001	0.030
<$20k	(0.097)	(0.098)	(0.097)	(0.099)	(0.093)	(0.097)	(0.087)	(0.093)	(0.072)	(0.079)	(0.055)	(0.062)
% with household income	0.285***	0.303***	0.257***	0.294***	0.178**	0.234***	0.152**	0.233***	0.103*	0.185***	0.046	0.102*
>$60k	(0.074)	(0.084)	(0.074)	(0.084)	(0.073)	(0.082)	(0.068)	(0.080)	(0.058)	(0.071)	(0.044)	(0.059)
% Black or Hispanic	-0.007	-0.008	-0.012	-0.012	-0.011	-0.011	-0.012	-0.011	-0.002	-0.001	0.007	0.008
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.012)	(0.012)	(0.009)	(0.009)
Number of municipalities	2.742	2.841	3.879*	4.088*	3.340	3.621	3.412	3.943*	3.196	3.845*	1.615	2.120
(1000s)	(2.105)	(2.097)	(2.327)	(2.309)	(2.363)	(2.347)	(2.209)	(2.256)	(1.977)	(2.046)	(1.359)	(1.425)
Constant	-0.101**	-0.106**	-0.065	-0.070	-0.045	-0.048	-0.059	-0.064	-0.063*	-0.070*	-0.077***	-0.083***
	(0.046)	(0.046)	(0.048)	(0.049)	(0.046)	(0.047)	(0.043)	(0.045)	(0.037)	(0.040)	(0.029)	(0.030)
Observations	293	291	293	291	293	291	293	291	293	291	293	291
Adjusted R^2	0.232	0.230	0.183	0.175	0.117	0.095	0.102	0.043	0.105	0.016	0.170	0.100
Underidentification p-value		0.000		0.000		0.000		0.000		0.000		0.000
Weak identification F-stat		18.693		18.693		18.693		18.693		18.693		18.693
Hansen J p-value		0.800		0.589		0.853		0.817		0.873		0.330

Notes: Unit of observation is MSA/PMSA with year 2000 boundaries. Dependent variable ranges from zero if no segregation to one if completely segregated. IVs are share of protective inspection expenditures and number of streams. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.4 Information Theory Index of Household Income: Wharton Residential Land Use Regulation Index (WRLURI) Subindexes

	Aspatial		500m radius		1000m radius		2000m radius		4000m radius		8000m radius	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Local Political Pressure	0.002	-0.029*	0.002	-0.033*	0.001	-0.037**	-0.000	-0.040**	-0.001	-0.043**	-0.000	-0.036**
Index (LPPI)	(0.003)	(0.017)	(0.003)	(0.018)	(0.002)	(0.018)	(0.002)	(0.018)	(0.002)	(0.018)	(0.001)	(0.015)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.277	-0.261	0.207	-0.537	0.132	-0.922	0.098	-1.408	0.104	-1.912	0.190	-1.952
Underidentification p-value		0.040		0.040		0.040		0.040		0.040		0.040
Weak identification F-stat		3.854		3.854		3.854		3.854		3.854		3.854
Hansen J p-value		0.744		0.676		0.910		0.524		0.452		0.757
State Political Involvement	-0.006***	-0.007	-0.006***	-0.008*	-0.007***	-0.010***	-0.007***	-0.012***	-0.006***	-0.013***	-0.005***	-0.010***
Index (SPII)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.002)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.318	0.316	0.256	0.252	0.205	0.194	0.183	0.137	0.202	0.118	0.274	0.190
Underidentification p-value		0.000		0.000		0.000		0.000		0.000		0.000
Weak identification F-stat		15.239		15.239		15.239		15.239		15.239		15.239
Hansen J p-value		0.111		0.065		0.207		0.513		0.523		0.209
State Court Involvement	0.002	-0.000	0.001	0.001	0.001	-0.007	0.001	-0.015	0.001	-0.016*	0.000	-0.008
Index (SCII)	(0.002)	(0.011)	(0.002)	(0.011)	(0.002)	(0.010)	(0.002)	(0.010)	(0.002)	(0.009)	(0.001)	(0.007)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.274	0.275	0.205	0.207	0.131	0.098	0.098	-0.081	0.104	-0.162	0.190	0.081
Underidentification p-value		0.003		0.003		0.003		0.003		0.003		0.003
Weak identification F-stat		7.315		7.315		7.315		7.315		7.315		7.315
Hansen J p-value		0.042		0.016		0.006		0.002		0.001		0.000
Local Zoning Approval	0.006***	0.036	0.006***	0.042*	0.005**	0.049**	0.005**	0.056**	0.004**	0.059***	0.003**	0.048***
Index (LZAI)	(0.002)	(0.024)	(0.002)	(0.024)	(0.002)	(0.023)	(0.002)	(0.023)	(0.002)	(0.023)	(0.001)	(0.018)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.292	-0.194	0.225	-0.509	0.151	-1.153	0.116	-2.162	0.118	-3.175	0.204	-3.039
Underidentification p-value		0.027		0.027		0.027		0.027		0.027		0.027
Weak identification F-stat		3.400		3.400		3.400		3.400		3.400		3.400
Hansen J p-value		0.476		0.408		0.774		0.867		0.835		0.852
Local Project Approval	0.004*	-0.024*	0.004*	-0.028*	0.004*	-0.028*	0.003*	-0.027*	0.002	-0.029*	0.001	-0.026**
Index (LPAI)	(0.002)	(0.014)	(0.002)	(0.015)	(0.002)	(0.016)	(0.002)	(0.016)	(0.002)	(0.015)	(0.001)	(0.013)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.282	-0.159	0.216	-0.419	0.143	-0.598	0.107	-0.739	0.110	-0.982	0.193	-1.094
Underidentification p-value		0.031		0.031		0.031		0.031		0.031		0.031
Weak identification F-stat		4.485		4.485		4.485		4.485		4.485		4.485
Hansen J p-value		0.676		0.666		0.352		0.120		0.079		0.173
Local Assembly Index (LAI)	-0.009	-0.199	-0.005	-0.228	-0.000	-0.277	0.006	-0.327	0.005	-0.346	0.000	-0.275
	(0.009)	(0.181)	(0.009)	(0.192)	(0.009)	(0.216)	(0.008)	(0.240)	(0.007)	(0.247)	(0.005)	(0.191)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.275	-0.750	0.206	-1.318	0.131	-2.702	0.100	-5.047	0.105	-7.056	0.190	-6.330
Underidentification p-value		0.290		0.290		0.290		0.290		0.290		0.290
Weak identification F-stat		1.047		1.047		1.047		1.047		1.047		1.047
Hansen J p-value		0.323		0.273		0.545		0.873		0.895		0.609
Density Restriction Index	0.011**	0.015	0.012**	0.015	0.011**	0.048	0.011***	0.082*	0.010**	0.089*	0.006**	0.054
(DRI)	(0.005)	(0.049)	(0.005)	(0.047)	(0.005)	(0.044)	(0.004)	(0.048)	(0.004)	(0.050)	(0.003)	(0.036)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.289	0.289	0.222	0.224	0.150	-0.038	0.122	-0.809	0.126	-1.325	0.204	-0.575
Underidentification p-value		0.161		0.161		0.161		0.161		0.161		0.161
Weak identification F-stat		2.314		2.314		2.314		2.314		2.314		2.314
Hansen J p-value		0.026		0.009		0.007		0.019		0.022		0.004
Open Space Index (OSI)	-0.001	-0.054	-0.001	-0.064*	-0.002	-0.074**	-0.003	-0.083**	-0.005	-0.088***	-0.005**	-0.072***
	(0.004)	(0.034)	(0.004)	(0.035)	(0.004)	(0.035)	(0.004)	(0.034)	(0.003)	(0.034)	(0.002)	(0.027)
Observations	293	291	293	291	293	291	293	291	293	291	293	291
Adjusted R^2	0.271	-0.168	0.202	-0.447	0.128	-0.890	0.097	-1.475	0.106	-2.028	0.197	-1.842
Underidentification p-value		0.024		0.024		0.024		0.024		0.024		0.024
Weak identification F-stat		4.362		4.362		4.362		4.362		4.362		4.362
Hansen J p-value		0.626		0.532		0.920		0.679		0.630		0.961
Exactions Index (EI)	0.009*	-0.006	0.007	-0.005	0.005	-0.022	0.001	-0.041*	-0.001	-0.044**	-0.000	-0.026
	(0.005)	(0.027)	(0.005)	(0.026)	(0.005)	(0.026)	(0.004)	(0.025)	(0.004)	(0.023)	(0.003)	(0.017)
Observations	293	291	293	291	293	291	293	291	293	291	293	291
Adjusted R^2	0.279	0.255	0.209	0.191	0.131	0.017	0.094	-0.235	0.099	-0.340	0.186	-0.042
Underidentification p-value		0.007		0.007		0.007		0.007		0.007		0.007
Weak identification F-stat		4.429		4.429		4.429		4.429		4.429		4.429
Hansen J p-value		0.043		0.015		0.008		0.004		0.001		0.000
Supply Restriction Index	-0.003	-0.026	-0.002	-0.030*	-0.002	-0.036*	-0.002	-0.042*	-0.001	-0.044*	-0.001	-0.035*
(SRI)	(0.002)	(0.016)	(0.002)	(0.018)	(0.002)	(0.020)	(0.002)	(0.024)	(0.002)	(0.025)	(0.001)	(0.021)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.278	-0.008	0.207	-0.245	0.134	-0.673	0.100	-1.358	0.106	-1.954	0.191	-1.818
Underidentification p-value		0.108		0.108		0.108		0.108		0.108		0.108
Weak identification F-stat		2.669		2.669		2.669		2.669		2.669		2.669
Hansen J p-value		0.247		0.204		0.517		0.912		0.937		0.585
Approval Delay Index (ADI)	-0.002***	-0.004**	-0.002***	-0.004**	-0.002***	-0.005***	-0.002***	-0.006***	-0.002***	-0.006***	-0.002***	-0.005***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.298	0.271	0.237	0.191	0.183	0.107	0.160	0.013	0.173	-0.054	0.249	0.009
Underidentification p-value		0.000		0.000		0.000		0.000		0.000		0.000
Weak identification F-stat		16.128		16.128		16.128		16.128		16.128		16.128
Hansen J p-value		0.400		0.294		0.749		0.685		0.593		0.849

Notes: Unit of observation is MSA/PMSA with year 2000 boundaries. Dependent variable ranges from zero if no segregation to one if completely segregated. IVs are share of protective inspection expenditures and number of streams. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.5 Information Theory Index of Poverty Threshold Ratio: Wharton Residential Land Use Regulation Index (WRLURI) Subindexes

	Aspatial		500m radius		1000m radius		2000m radius		4000m radius		8000m radius	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Local Political Pressure	0.001	-0.015	0.001	-0.021	-0.001	-0.026	-0.002	-0.033*	-0.002	-0.035*	-0.001	-0.029*
Index (LPPI)	(0.003)	(0.017)	(0.003)	(0.018)	(0.003)	(0.018)	(0.002)	(0.019)	(0.002)	(0.019)	(0.001)	(0.016)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.229	0.131	0.178	0.003	0.105	-0.201	0.091	-0.472	0.089	-0.746	0.154	-0.730
Underidentification p-value		0.040		0.040		0.040		0.040		0.040		0.040
Weak identification F-stat		3.854		3.854		3.854		3.854		3.854		3.854
Hansen J p-value		0.945		0.786		0.908		0.599		0.607		0.666
State Political Involvement	-0.008***	-0.004	-0.007***	-0.005	-0.008***	-0.007*	-0.007***	-0.010**	-0.007***	-0.010***	-0.005***	-0.007**
Index (SPII)	(0.002)	(0.005)	(0.002)	(0.005)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.003)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.272	0.262	0.222	0.219	0.163	0.168	0.148	0.153	0.151	0.146	0.205	0.203
Underidentification p-value		0.000		0.000		0.000		0.000		0.000		0.000
Weak identification F-stat		15.239		15.239		15.239		15.239		15.239		15.239
Hansen J p-value		0.587		0.379		0.536		0.700		0.578		0.111
State Court Involvement	-0.001	-0.001	-0.002	0.001	-0.002	-0.005	-0.002	-0.012	-0.001	-0.012	0.000	0.001
Index (SCII)	(0.003)	(0.012)	(0.003)	(0.012)	(0.003)	(0.012)	(0.003)	(0.012)	(0.002)	(0.011)	(0.002)	(0.009)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.228	0.230	0.179	0.179	0.107	0.106	0.090	0.043	0.086	0.017	0.152	0.152
Underidentification p-value		0.003		0.003		0.003		0.003		0.003		0.003
Weak identification F-stat		7.315		7.315		7.315		7.315		7.315		7.315
Hansen J p-value		0.365		0.201		0.114		0.045		0.019		0.008
Local Zoning Approval	0.007**	0.020	0.007**	0.026	0.006**	0.035	0.005*	0.046**	0.004*	0.049**	0.003**	0.036**
Index (LZAI)	(0.003)	(0.023)	(0.003)	(0.023)	(0.003)	(0.023)	(0.003)	(0.023)	(0.002)	(0.022)	(0.002)	(0.018)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.245	0.190	0.194	0.064	0.121	-0.216	0.103	-0.713	0.098	-1.215	0.163	-0.995
Underidentification p-value		0.027		0.027		0.027		0.027		0.027		0.027
Weak identification F-stat		3.400		3.400		3.400		3.400		3.400		3.400
Hansen J p-value		0.792		0.613		0.874		0.875		0.929		0.438
Local Project Approval	0.007**	-0.012	0.007**	-0.018	0.006**	-0.019	0.005*	-0.022	0.003	-0.024	0.002	-0.025*
Index (LPAI)	(0.003)	(0.015)	(0.003)	(0.016)	(0.003)	(0.017)	(0.002)	(0.017)	(0.002)	(0.016)	(0.001)	(0.014)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.244	0.119	0.194	-0.020	0.122	-0.158	0.100	-0.267	0.093	-0.437	0.156	-0.615
Underidentification p-value		0.031		0.031		0.031		0.031		0.031		0.031
Weak identification F-stat		4.485		4.485		4.485		4.485		4.485		4.485
Hansen J p-value		0.748		0.791		0.485		0.208		0.176		0.668
Local Assembly Index (LAI)	-0.010	-0.109	-0.009	-0.141	-0.003	-0.196	0.004	-0.267	0.003	-0.284	-0.001	-0.197
	(0.011)	(0.148)	(0.011)	(0.152)	(0.011)	(0.170)	(0.010)	(0.200)	(0.010)	(0.200)	(0.007)	(0.143)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.230	0.054	0.179	-0.145	0.105	-0.722	0.090	-1.866	0.086	-2.832	0.152	-2.010
Underidentification p-value		0.290		0.290		0.290		0.290		0.290		0.290
Weak identification F-stat		1.047		1.047		1.047		1.047		1.047		1.047
Hansen J p-value		0.684		0.498		0.704		0.917		0.845		0.290
Density Restriction Index	0.010*	0.013	0.009	0.008	0.009	0.036	0.010*	0.068	0.008*	0.068	0.005	0.012
(DRI)	(0.006)	(0.053)	(0.006)	(0.053)	(0.006)	(0.053)	(0.005)	(0.056)	(0.005)	(0.054)	(0.003)	(0.039)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.235	0.238	0.185	0.188	0.113	0.061	0.099	-0.246	0.096	-0.387	0.158	0.153
Underidentification p-value		0.161		0.161		0.161		0.161		0.161		0.161
Weak identification F-stat		2.314		2.314		2.314		2.314		2.314		2.314
Hansen J p-value		0.354		0.193		0.127		0.094		0.061		0.010
Open Space Index (OSI)	0.003	-0.031	0.003	-0.042	0.003	-0.055	0.002	-0.070*	-0.001	-0.075**	-0.002	-0.057*
	(0.006)	(0.035)	(0.006)	(0.037)	(0.005)	(0.037)	(0.005)	(0.038)	(0.004)	(0.037)	(0.003)	(0.031)
Observations	293	291	293	291	293	291	293	291	293	291	293	291
Adjusted R^2	0.225	0.113	0.176	-0.031	0.106	-0.290	0.090	-0.639	0.085	-0.951	0.150	-0.778
Underidentification p-value		0.024		0.024		0.024		0.024		0.024		0.024
Weak identification F-stat		4.362		4.362		4.362		4.362		4.362		4.362
Hansen J p-value		0.853		0.661		0.936		0.760		0.801		0.490
Exactions Index (EI)	0.007	-0.006	0.008	-0.002	0.006	-0.016	0.003	-0.034	0.001	-0.033	0.001	-0.003
	(0.007)	(0.029)	(0.006)	(0.029)	(0.006)	(0.030)	(0.005)	(0.029)	(0.004)	(0.026)	(0.003)	(0.021)
Observations	293	291	293	291	293	291	293	291	293	291	293	291
Adjusted R^2	0.229	0.217	0.180	0.175	0.108	0.065	0.090	-0.051	0.085	-0.079	0.150	0.147
Underidentification p-value		0.007		0.007		0.007		0.007		0.007		0.007
Weak identification F-stat		4.429		4.429		4.429		4.429		4.429		4.429
Hansen J p-value		0.342		0.174		0.104		0.052		0.020		0.007
Supply Restriction Index	-0.004	-0.014	-0.003	-0.018	-0.003	-0.025	-0.002	-0.034	-0.002	-0.036	-0.001	-0.026
(SRI)	(0.003)	(0.017)	(0.003)	(0.018)	(0.003)	(0.020)	(0.003)	(0.025)	(0.002)	(0.026)	(0.002)	(0.022)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.233	0.199	0.180	0.096	0.109	-0.100	0.092	-0.417	0.089	-0.708	0.153	-0.510
Underidentification p-value		0.108		0.108		0.108		0.108		0.108		0.108
Weak identification F-stat		2.669		2.669		2.669		2.669		2.669		2.669
Hansen J p-value		0.690		0.499		0.725		0.957		0.878		0.283
Approval Delay Index (ADI)	-0.002**	-0.002	-0.002**	-0.003	-0.002***	-0.003*	-0.002***	-0.005**	-0.002***	-0.005**	-0.001***	-0.004**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.000)	(0.002)
Observations	295	293	295	293	295	293	295	293	295	293	295	293
Adjusted R^2	0.241	0.239	0.194	0.188	0.132	0.115	0.118	0.062	0.120	0.026	0.186	0.105
Underidentification p-value		0.000		0.000		0.000		0.000		0.000		0.000
Weak identification F-stat		16.128		16.128		16.128		16.128		16.128		16.128
Hansen J p-value		0.806		0.605		0.897		0.773		0.823		0.339

Notes: Unit of observation is MSA/PMSA with year 2000 boundaries. Dependent variable ranges from zero if no segregation to one if completely segregated. IVs are share of protective inspection expenditures and number of streams. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.6 Information Theory Index of White-Black Residential Segregation: Wharton Residential Land Use Regulation Index (WRLURI)

	Aspatial		500m radius		1000m radius		2000m radius		4000m radius		8000m radius	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
WRLURI	-0.025***	-0.025	-0.024***	-0.025	-0.028***	-0.032	-0.030***	-0.042*	-0.031***	-0.048**	-0.028***	-0.048***
	(0.007)	(0.019)	(0.007)	(0.019)	(0.008)	(0.021)	(0.008)	(0.022)	(0.007)	(0.020)	(0.005)	(0.015)
Log population	0.052***	0.052***	0.051***	0.052***	0.050***	0.050***	0.050***	0.050***	0.048***	0.048***	0.043***	0.042***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
Gini	0.494	0.422	0.505	0.426	0.625*	0.535	0.552*	0.440	0.328	0.221	0.060	-0.037
	(0.321)	(0.336)	(0.323)	(0.339)	(0.334)	(0.353)	(0.329)	(0.352)	(0.293)	(0.319)	(0.243)	(0.273)
% with household income	0.726**	0.769***	0.661**	0.708**	0.551*	0.607**	0.555*	0.634**	0.463*	0.545**	0.334	0.415*
<$20k	(0.284)	(0.291)	(0.284)	(0.291)	(0.291)	(0.301)	(0.283)	(0.298)	(0.249)	(0.268)	(0.206)	(0.229)
% with household income	0.394**	0.433*	0.331*	0.376	0.223	0.289	0.215	0.334	0.199	0.342	0.178	0.332*
>$60k	(0.198)	(0.234)	(0.198)	(0.236)	(0.209)	(0.251)	(0.206)	(0.256)	(0.184)	(0.236)	(0.153)	(0.199)
% Black or Hispanic	-0.023	-0.024	-0.014	-0.015	-0.008	-0.009	-0.000	0.000	0.015	0.018	0.013	0.016
	(0.038)	(0.037)	(0.037)	(0.037)	(0.038)	(0.037)	(0.038)	(0.038)	(0.036)	(0.036)	(0.028)	(0.028)
Number of municipalities	14.061***	13.633**	13.936***	13.492**	12.764**	12.583**	12.002**	12.558**	10.208**	11.361**	6.685**	8.224**
(1000s)	(5.271)	(5.374)	(5.236)	(5.338)	(5.378)	(5.579)	(5.197)	(5.643)	(4.362)	(4.950)	(3.314)	(3.877)
Constant	-0.847***	-0.838***	-0.814***	-0.805***	-0.822***	-0.815***	-0.845***	-0.849***	-0.747***	-0.761***	-0.577***	-0.598***
	(0.124)	(0.124)	(0.119)	(0.120)	(0.116)	(0.118)	(0.114)	(0.118)	(0.105)	(0.109)	(0.089)	(0.092)
Observations	293	291	293	291	293	291	293	291	293	291	293	291
Adjusted R^2	0.360	0.357	0.354	0.350	0.330	0.323	0.324	0.310	0.333	0.311	0.355	0.318
Underidentification p-value		0.000		0.000		0.000		0.000		0.000		0.000
Weak identification F-stat		18.693		18.693		18.693		18.693		18.693		18.693
Hansen J p-value		0.185		0.248		0.178		0.111		0.208		0.678

Notes: Unit of observation is MSA/PMSA with year 2000 boundaries. Dependent variable ranges from zero if no segregation to one if completely segregated. IVs are share of protective inspection expenditures and number of streams. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.1. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Permitted New Housing Units Per 100,000 People	32,144	231.766	307.882	0.000	15,786.530
$\sinh^{-1}$ Permitted New Housing Units Per 100,000 People	32,144	5.227	1.873	0.000	10.360
Homestead Assessment Cap	30,817	0.260	0.439	0.000	1.000
Homestead Assessment Cap Rate	7,553	6.321	4.504	-0.300	15.000
Use/Size/Zoning Resets Homestead Assessment Cap	30,817	0.148	0.355	0.000	1.000
Assessment Cap x Appreciation Rate	23,120	0.312	2.609	-24.286	42.566
Assessment Cap Rate x Appreciation Rate	5,266	14.015	37.103	-220.184	425.662
Use/Size/Zoning Resets Cap x Appreciation Rate	23,120	0.270	2.102	-21.512	42.566
Assessment Cap x Property Tax Rate	32,144	0.690	2.381	0.000	100.659
Assessment Cap Rate x Property Tax Rate	7,553	21.559	44.298	-1.428	1,006.591
Use/Size/Zoning Resets Cap x Property Tax Rate	32,144	0.479	2.323	0.000	100.659
Appreciation Rate x Property Tax Rate	23,120	4.864	36.441	-1,697.992	2,679.246
Assessment Cap x Appreciation Rate x Tax Rate	23,120	1.592	24.651	-556.077	2,008.052
Assessment Cap Rate x Appreciation Rate x Tax Rate	5,266	72.057	506.237	-5,560.766	20,080.530
Use/Size/Zoning Resets Cap x Appreciation Rate x Tax Rate	23,120	1.557	24.388	-556.077	2,008.052
Appreciation Rate of Median Home Value	23,120	1.608	4.462	-26.923	60.640
Median Home Value ($100,000s)	26,128	1.360	0.838	0.294	10.000
Property Tax Rate	32,144	2.497	4.770	0.000	270.880
Population (100,000s)	32,144	1.066	3.306	0.004	101.057
Median Household Income ($10,000s)	32,144	4.771	1.278	1.897	14.230
Unemployment Rate	32,144	0.074	0.034	0.000	0.290
Percent Black or Hispanic	32,144	0.172	0.181	0.000	0.992
Percent Age 0-17	32,144	0.230	0.034	0.039	0.433
Percent Age 65+	32,144	0.167	0.044	0.024	0.567

Notes: Unit of observation is county for each year 2007-2017.

Table 2.2 State-Level Treatment Results: Permitted New Housing Units Per 100,000 People

	Level		Inverse Hyperbolic Sine	
	(1)	(2)	(3)	(4)
Homestead Assessment Cap	18.279		-0.009	
	(11.835)		(0.052)	
Use/Size/Zoning Change Resets Homestead Assessment Cap		18.279		-0.009
		(11.835)		(0.052)
Local Option For Assessment Cap	36.896***	36.896***	0.190**	0.190**
	(7.949)	(7.949)	(0.093)	(0.093)
Property Tax Rate	-1.860	-1.860	-0.002	-0.002
	(1.205)	(1.205)	(0.010)	(0.010)
Population (100,000 people)	99.401***	99.401***	0.407***	0.407***
	(24.923)	(24.923)	(0.080)	(0.080)
Median Household Income ($10,000s, current dollars)	92.283***	92.283***	0.254***	0.254***
	(20.973)	(20.973)	(0.041)	(0.041)
Unemployment Rate	-621.399***	-621.399***	-2.220***	-2.220***
	(102.713)	(102.713)	(0.669)	(0.669)
Percent Black or Hispanic	-523.615***	-523.615***	-0.284	-0.284
	(196.586)	(196.586)	(1.034)	(1.034)
Percent Age 0-17	-946.350***	-946.350***	-1.448	-1.448
	(351.765)	(351.765)	(1.745)	(1.745)
Percent Age 65+	-1481.620***	-1481.620***	-1.671	-1.671
	(430.230)	(430.230)	(1.286)	(1.286)
Census Division-Year Effects	X	X	X	X
County Fixed Effects	X	X	X	X
Observations	32144	32144	32144	32144
Adjusted R2	0.143	0.143	0.073	0.073

Notes: Unit of observation is county for each year 2007-2017. Standard errors, clustered at the county level, are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table 2.3 County-Level Treatment Results: Number of Permitted New Housing Units Per 100,000 People

		Homestead Assessment Cap			Use/Size/Zoning Resets Cap		Homestead Assessment Cap Rate		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Homestead Assessment Cap Policy	42.513*	-34.586	-28.842	-19.076	-28.842	-18.588	4.144	-0.256	-0.536
	(25.324)	(27.890)	(19.724)	(20.072)	(19.724)	(20.057)	(4.737)	(7.041)	(7.677)
Homestead Assessment Cap Policy x Appreciation Rate				-2.026		-3.375			0.010
				(2.912)		(2.301)			(0.149)
Homestead Assessment Cap Policy x Property Tax Rate				-1.627		-1.200			0.371
				(1.014)		(0.845)			(1.264)
Appreciation Rate x Property Tax Rate				-0.017		-0.017			0.770
				(0.130)		(0.127)			(0.698)
Cap Policy x Appreciation Rate x Property Tax Rate				0.024		0.064			-0.074
				(0.129)		(0.121)			(0.071)
Appreciation Rate of Median Home Value		3.953**	4.397**	5.088	4.397**	5.081*		2.720***	2.030
		(1.813)	(2.023)	(3.048)	(2.023)	(2.652)		(0.712)	(1.491)
Median Home Value ($100,000s, current dollars)			-157.845*	-158.447*	-157.845*	-156.630**		-55.174	-54.373
			(78.859)	(79.093)	(78.859)	(77.967)		(61.811)	(63.039)
Property Tax Rate	-1.589	-2.285**	-2.387**	-2.007***	-2.387**	-2.096***	-3.557*	-3.863**	-7.492
	(1.262)	(0.963)	(0.932)	(0.721)	(0.932)	(0.747)	(1.900)	(1.397)	(12.670)
Population (100,000 people)	94.722***	173.222***	171.616***	175.732***	171.616***	173.389***	64.878***	125.255***	123.644***
	(31.115)	(43.835)	(41.878)	(39.863)	(41.878)	(41.549)	(16.724)	(28.367)	(28.855)
Median Household Income ($10,000s, current dollars)	93.748***	73.536***	86.200***	85.954***	86.200***	86.275***	56.404***	70.568**	71.249**
	(34.541)	(17.085)	(23.064)	(22.635)	(23.064)	(22.993)	(15.999)	(25.359)	(25.978)
Unemployment Rate	-643.861***	-513.573***	-328.426**	-340.505**	-328.426**	-333.192**	-242.267	-212.520	-202.291
	(166.720)	(152.014)	(146.928)	(143.652)	(146.928)	(148.062)	(178.018)	(344.497)	(356.379)
Percent Black or Hispanic	-577.940**	-696.212	-828.323	-821.105	-828.323	-822.674	-49.326	151.948	126.840
	(259.835)	(513.142)	(515.738)	(507.697)	(515.738)	(515.200)	(296.606)	(294.414)	(288.737)
Percent Age 0-17	-1017.783**	-1343.262**	-1115.573**	-1121.302**	-1115.573**	-1125.196**	28.685	-884.635*	-856.947*
	(437.610)	(586.341)	(433.100)	(440.219)	(433.100)	(443.324)	(343.138)	(472.528)	(422.517)
Percent Age 65+	-1461.407***	299.924	158.297	147.895	158.297	143.523	-1165.788	-13.220	54.639
	(506.094)	(379.743)	(425.634)	(428.968)	(425.634)	(430.600)	(852.653)	(1112.060)	(1101.162)
Census Division-Year Effects (many omitted for collinearity)	X	X	X	X	X	X	X	X	X
County Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	30817	22103	22103	22103	22103	22103	7553	5266	5266
Adjusted R2	0.131	0.074	0.080	0.080	0.080	0.081	0.212	0.169	0.169

Notes: Unit of observation is county for each year 2007-2017 (column 1) and 2010-2017 (columns 2-8). Georgia counties are excluded for all years except 2009 and 2010. Standard errors, clustered at the state level, are in parentheses.

* p<0.10, ** p<0.05, *** p<0.01.

Table 2.4 County-Level Treatment Results: Inverse Hyperbolic Sine of Permitted New Housing Units Per 100,000 People

		Homestead Assessment Cap			Use/Size/Zoning Resets Cap		Homestead Assessment Cap Rate		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Homestead Assessment Cap Policy	0.058	-0.581***	-0.562***	-0.671***	-0.562***	-0.666***	0.030	0.002	0.011
	(0.099)	(0.176)	(0.146)	(0.157)	(0.146)	(0.156)	(0.030)	(0.036)	(0.042)
Homestead Assessment Cap Policy x Appreciation Rate				0.007*		0.008**			0.001
				(0.004)		(0.004)			(0.001)
Homestead Assessment Cap Policy x Property Tax Rate				0.032***		0.031***			-0.002
				(0.010)		(0.009)			(0.006)
Appreciation Rate x Property Tax Rate				0.000***		0.000***			0.008
				(0.000)		(0.000)			(0.006)
Cap Policy x Appreciation Rate x Property Tax Rate				-0.000***		-0.000***			-0.001
				(0.000)		(0.000)			(0.001)
Appreciation Rate of Median Home Value		0.010***	0.011***	0.008***	0.011***	0.009***		0.013***	-0.001
		(0.002)	(0.002)	(0.003)	(0.002)	(0.003)		(0.004)	(0.011)
Median Home Value ($100,000s, current dollars)			-0.519***	-0.518***	-0.519***	-0.522***		-0.238	-0.237
			(0.138)	(0.137)	(0.138)	(0.137)		(0.191)	(0.192)
Property Tax Rate	-0.001	0.002	0.002	-0.006	0.002	-0.005	0.037***	0.028***	0.047
	(0.013)	(0.010)	(0.010)	(0.008)	(0.010)	(0.008)	(0.008)	(0.004)	(0.064)
Population (100,000 people)	0.387***	0.392***	0.387***	0.381***	0.387***	0.388***	0.275***	0.199***	0.196***
	(0.106)	(0.117)	(0.104)	(0.105)	(0.104)	(0.104)	(0.072)	(0.049)	(0.051)
Median Household Income ($10,000s, current dollars)	0.259***	0.155***	0.197***	0.196***	0.197***	0.194***	0.200***	0.216***	0.225***
	(0.047)	(0.041)	(0.043)	(0.044)	(0.043)	(0.044)	(0.055)	(0.062)	(0.066)
Unemployment Rate	-2.350***	-1.419	-0.809	-0.812	-0.809	-0.842	-2.695	-1.634	-1.629
	(0.747)	(0.889)	(0.906)	(0.918)	(0.906)	(0.907)	(1.488)	(2.548)	(2.628)
Percent Black or Hispanic	-0.342	-2.437	-2.871	-2.864	-2.871	-2.862	2.608***	0.873	0.740
	(1.292)	(1.911)	(1.876)	(1.876)	(1.876)	(1.878)	(0.822)	(0.499)	(0.415)
Percent Age 0-17	-1.664	-2.329	-1.580	-1.477	-1.580	-1.464	-1.721	-7.637	-7.792
	(1.181)	(2.456)	(2.548)	(2.519)	(2.548)	(2.526)	(1.779)	(6.750)	(6.522)
Percent Age 65+	-1.750	0.552	0.086	0.204	0.086	0.207	-3.093	-3.142	-2.893
	(1.409)	(1.893)	(1.925)	(1.914)	(1.925)	(1.915)	(2.851)	(5.136)	(5.143)
Census Division-Year Effects (many omitted for collinearity)	X	X	X	X	X	X	X	X	X
County Fixed Effects	X	X	X	X	X	X	X	X	X
Observations	30817	22103	22103	22103	22103	22103	7553	5266	5266
Adjusted R2	0.067	0.022	0.024	0.024	0.024	0.024	0.082	0.034	0.034

Notes: Unit of observation is county for each year 2007-2017 (column 1) and 2010-2017 (columns 2-8). Georgia counties are excluded for all years except 2009 and 2010. Standard errors, clustered at the state level, are in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.