"Zoned out of Opportunity": Causal Effect of Land Use Regulation on Adult Incomes

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Abstract

This paper uses a novel natural language processing technique — denominated *concept recovery* — to extract latent variables from the text of a large corpus of municipal regulations, in particular three 'concepts' relating to land use: 1) restrictions on intensive and extensive development, 2) minimum consumption requirements, and 3) 'regulatory taxes' (i.e. regulations that do not interdict development, but make it more expensive). With these estimands, we derive estimates of the causal effect of land-use regulations on the incomes in adulthood of children born in 2000 that grow up in urbanized areas. We find that land-use regulations have clear distributional consequences, advantaging children born to parents in the 75th percentile of the income distribution, while disadvantaging children born to parents in the 25th percentile of the income distribution.

[*]Replication materials are available at the following GitHub Repository, 3,734 lines of code and counting.

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Contents

1 Introduction

> *"It is true that when, if ever, the provisions set forth in the ordinance in tedious and minute detail, come to be concretely applied to particular conditions ... some of them, or even many of them, may be found to be clearly arbitrary and unreasonable."*
>
> — Village of Euclid v. Ambler Realty Company (1926)

Zoning laws — and land-use regulations, generally — are creatures of the early 20th century, a stopgap legal measure implemented by municipalities as a defense against the harshest features of industrialization and mechanization. These laws were rationalized then as necessary to the continued existence of prosperous residential areas and defended as mere extensions of a locality's 'police powers,' that is, its vested authority to implement and enforce all statutes and regulations consistent with the aims of bettering the public health, safety, and morals.[1]

Now, far from defense against certain inexorable economic processes, land use regulation has become a bulwark of local power. In fact, it is claimed with certain regularity by observers that zoning is the single most important power exercised by local government, bar none. [2] Rather than serving as a response to urban economic conditions, land-use regulations create these conditions, influencing the tenor and character of urban development. As few limitations exist on a community's power to regulate the built environment, and as laws are often constructed without regard to their global consequences — economic or otherwise — the potential for misuse is significant. Consequently, if regulations are binding, they are liable to be distortionary, engendering welfare and distributional effects, which remain

[1] It is, perhaps, miraculous that the Supreme Court of the United States, in the throes of the now widely derided *Lochner* doctrine (which held that most economic regulations violated the 14th Amendment), accepted this exact argument in *Euclid v. Ambler* (1926), which held that municipalities enjoyed an uncabined right to implement land-use regulations.

[2] Here, Edward Glaeser makes this exact point.

relatively understudied.

The object of this paper is to study the potential impact of land-use regulations on an outcome of general import and specific relevance to the American self-concept: intergenerational economic mobility. Throughout this paper, we will develop the foundations for an estimate of the causal effect of land-use regulations on the incomes in adulthood of children born in urbanized areas in the United States in the year 2000, conditional on the income rank of their parents.

To do so, we first appeal to a theoretical model, which elucidates the functional relationship between jurisdictional fragmentation — that is to say, the degree to which an urbanized area is divided among various localities — and the prevailing regulatory environment at the citywide level. We derive testable implications from the theory, which factor into the empirical analysis performed later on.

Next, we develop an understanding of the econometric toolkit used to perform the data analysis. In particular, we describe a novel natural language processing technique that allows the researcher to *read* certain concepts into text data, which we call 'concept recovery.' Given a collection of real-world outcomes and text for a subsample of the data, we show how one can extract latent variables that scale in the degree to which a certain concept is inscribed in a document. Concretely, given a large a corpus of municipal codes (22,963 laws representing 2,612 unique local governments and spanning 23 years) and the response to survey questions for a subsample of these (drawn from Gyourko et al. [2021]), we estimate the degree to which municipalities implement restrictions on intensive and extensive development, prescribe a level of minimum housing consumption, and forestall development, either by making it more costly or by increasing uncertainty around approval. Lastly, using these estimands as inputs in our statistical model, we estimate the effect of an exogenous change in land-use regulations citywide on the estimated incomes of children who grow up and reside in those cities, conditional on parental income percentile and various Census tract-level covariates.

Using a Heckman selection model (to account for potential unobserved factors in the selection of municipalities into our sample), we analyze the determinants of land-use regulations, that is to say, the economic or demographic characteristics that influence the regulatory preferences of a community. Our most robust finding is that counties (as opposed to municipal governments) possess less robust land-use regimes, conforming to the theoretical results of Ortalo-Magné and Prat [2014]. On the question of race, we find that the ethnic or racial composition of communities is, by and large, not determinative of regulatory regimes but that communities that are whiter than their surroundings do, in fact, regulate land more heavily, lending credence to the widely held belief that zoning principally serves an exclusionary purpose. Lastly, we find that regulatory preferences are independent of the percentage of the population that are homeowners or possess tertiary degrees, a result orthogonal to the existing literature.

Reviewing the main results of the paper, we find that our instrument — a measure of jurisdictional fragmentation — is relevant for all of our regulatory estimands, suggesting that intra-jurisdictional competition (à la Tiebout) influences the regulatory decisions of individual governments. Furthermore, we find that regulatory indices are decreasing in fragmentation, indicating that concentration in the provision of public goods alters the economic calculus for municipalities. The proposed mechanism is akin to that of the competition of firms, where 'market power' grants large firms the ability to introduce discretion in their pricing decisions.

The headline result is that land-use regulations have a differential impact on the expected incomes of children born to parents in the 25th percentile and children born to parents in the 75th percentile of the income distribution. In this way, land-use regulations have distributional consequences, increasing the prospects of rich children at the expense of their poorer counterparts. In particular, we find that all else equal, a one standard deviation increase in the intensity of density restrictions corresponds to a $787 decline in annual earnings for poorer children and a \$1,260 increase in annual earnings for wealthier children. Using the Wharton Residential Land Use Regulatory Index (WRLURI) of Gyourko et al. [2021], we find the opposite effect, with a one standard deviation increase in this measure corresponding to a \$524 increase in the annual incomes of poorer children and a \$1,109 decrease in the annual incomes of wealthier children. These results suggest that, though specific land regulations have an adverse distributional consequence (namely, the ones considered in this paper), robust land-use regimes need not promote this end.

We next propose several channels through which land-use regulations affect the incomes in adulthood of children: 1) through its effect on the price of residing in a neighborhood with favorable conditions for upward mobility, 2) through its effect on the financial decisions of local governments, and 3) through its effect on the types of housing that are available in the urbanized area. We denominate these three channels as the 'price of opportunity,' 'government finances,' and 'housing misspecification' channels, respectively. First, we find that increasing the 'price of opportunity' uniformly decreases expected adult incomes, that increasing public expenditures per capita increases expected adult incomes, and that increasing the share of single-family houses (our measure of 'housing misspecification') decreases expected adult incomes. Further, we find that around 71% of our estimate of the effect of the WRLURI on the expected incomes of poor children can be accounted for by these three channels, while the effect of other policies remains, in large part, unexplained.

While this work is far from exhaustive, its results suggest that specific land-use regulations may have adverse implications for the ability of poorer children to rise the income ladder. We hope these findings will serve to hasten the arrival of a more equitable and less restrictive future for urban policymaking and that it will inspire other researchers to take up similar questions.

2 Literature Review

The following paper contributes to four strands of the literature: 1) literature on the measurement of land-use regulations, 2) literature on the determinants of land-use regulations, 3) literature on the effects of land-use regulations and their welfare implications, and 4) literature on intergenerational income dynamics.

Measurement of land-use regulations

land-use regulations are notoriously difficult to measure, for one, because honing in on one type of regulation (while disregarding others) provides a misleading picture of the regulatory environment when communities can use regulations as substitutes for one another.

Building on standard neoclassical theory, which implies that price equals average cost in a competitive market, Glaeser et al. [2005] argues that a large gap between prices and marginal construction costs signals that a market is tightly regulated. If the marginal cost function is increasing, regulation would imply that prices and average costs sit above marginal costs. Exploiting this result, the author takes the difference between market prices in Manhattan and the marginal cost of building an additional floor as a proxy of the 'bindingness' of land-use regulations, finding that prices are more than twice their supply costs.

Adopting a different approach, Glaeser et al. [2006] and Glaeser and Ward [2009] perform a detailed analysis of local zoning laws in the Greater Boston Area, manually extracting discrete provisions from each community's code. Their most robust finding concerns the effect of minimum lot sizes, estimating that an increase in this quantity by a quarter-acre corresponds to a roughy 10% decline in the number of houses permitted over time. They also find that strict wetlands regulations effectively constrain new development.

The seminal paper in this strand is Gyourko et al. [2008] (and its follow-up Gyourko et al.

[2021]), which proposes the Wharton Residential Land Use Regulatory Index (WRLURI). In this work, the responses from a survey on land-use regulations from about 2,600 communities across the U.S. were used to develop a series of indexes that captured the stringency of local regulatory environments. Factor analysis was then used to combine the component indices into a statistic which allowed for comparison of communities across a single measure. (In this work, we use the responses to this survey from the latest wave as inputs in an unstructured natural language processing model.)

More recently, Ganong and Shoag [2017] constructs a panel of land-use regulations using a scaled count of the number of appeals and supreme court decisions in each state that mention “land use” as a proxy for stringency.

Determinants of land-use regulations

Perhaps the most important conceptual framework for the determinants of land-use regulations is the ‘Homevoter Hypothesis’ from Fischel [2005], which argues that when local amenities and disamenities are capitalized into home values, owners have a strong incentive to restrict undesired development, as their home — their largest source of wealth — is uninsured against unsolicited declines in equity. As a corollary, Fischel observes that as homeowners typically work in nearby jurisdictions, they can, in principle, push development to neighboring communities, reaping the positive effects of job creation without incurring the costs imposed by higher density in their own neighborhoods.

While the ‘Hypothesis’ has proven influential, there exists both inclusive and exclusive empirical evidence. Brueckner [1998], and Logan et al. [2000] both find that homeownership shares and growth restrictions are related, albeit weakly. Hilber and Robert-Nicoud [2013] instrument for the homeownership share with the fraction of households that are married couples with no children, finding no correlation with the WRLURI. Glaeser and Ward [2009] examine patterns of housing supply regulation as a function of homeownership rates in 1940 and 1970, concluding that there is a weak correlation between historical homeownership rates and the intensity of land-use regulations.

Though the homeownership rate does not seem to be a strong determinant of land-use regulations, evidence has emerged that the demographic and economic characteristics of a community are influential. Gyourko et al. [2008] and Gyourko et al. [2021] suggest that measures of community wealth — including income and educational attainment — are strongly positively correlated with stricter land-use regulations and that population density is weakly correlated with the WRLURI. Building on this work, Saiz [2010] finds a strong link between the WRLURI and natural constraints on developable land, suggesting that anti-growth policies are more likely to arise in land-constrained metropolitan areas.

There is also some evidence that land-use regulations may serve an exclusionary end. Hamilton [1978] suggests that zoning arises out of a desire to limit the 'fiscal externality' engendered when households pay a tax that is proportional to their income but share in the benefits of public expenditures equally. Similarly, Rolleston [1987] finds that communities comprised of a lower percentage of minority residents relative to other jurisdictions in the urbanized area tend to have more restrictive zoning laws in place. Bates and Santerre [1994] find that when a community has lower levels of poverty than the nearest city, a smaller fraction of available land is zoned for residential use.

Effects of land-use regulations and Welfare Implications

Several papers have studied the effects of land-use regulations on economic outcomes and the implications these have for welfare and allocative efficiencies.

In earlier work, Levine [1999] finds that, controlling for 1980 income, cities that enacted more growth control measures between 1979 and 1988 had higher incomes in 1990, lending credence to the notion that zoning affects sorting by income. Similarly, Gyourko et al. [2013] finds that when households have constant preferences over location and the supply of places to live is not perfectly elastic everywhere, a change in aggregate housing demand (a "national demand shock" as it were) results in a larger share of high-income residents living in highly regulated areas. Furthermore, Ganong and Shoag [2017] shows that supply inelasticites engendered by zoning laws in high-income places deter low-skilled migration, slowing income convergence. Lastly, Hsieh and Moretti [2019] demonstrate that land-use regulations lead to large spatial misallocations of labor between cities, diverting population away from high productivity cities with strict zoning laws towards lower productivity cities with a more elastic housing supply. They estimate that these constraints lowered aggregate economic growth in the United States by 36% from 1964 to 2009.

In the domain of welfare economics, Ortalo-Magné and Prat [2014] suggests that land-use constraints diminish total welfare as they reduce the number of housing units but do not create any local amenities that would compensate for this negative effect. Using the WRLURI and a national dataset of transaction-level land sales, Turner et al. [2014] corroborate this result, suggesting that land-use regulations lower land prices by as much as 36%, leading to significant welfare losses.

Intergenerational Income Dynamics

This paper fits squarely within the literature on the role of *place* in influencing intergenerational income dynamics. Perhaps the first paper in the modern literature on the geography of intergenerational mobility in the United States is Chetty et al. [2014], which finds substantial variation in relative mobility (that is to say, how children fare compared to members of their own birth cohort) and absolute mobility (that is to say how children fare compared to their parents) across commuting zones. They suggest that there are five factors that (endogenously) drive this spatial variation in upward mobility: racial segregation, income inequality, school quality, the strength of social networks, and family structure. Furthermore, they find that upward mobility is only weakly correlated with local tax policies, rates of migration, and access to higher education.

In line with this paper, Chetty et al. [2018] constructs Census tract-level estimates of children's incomes in adulthood, conditional on parental income percentile (from which the data for this paper is in part derived). They assign children to locations by the proportion of time they spent growing up in a particular tract. Similarly, they find significant variation in children's outcomes in adulthood, nationally, between urbanized areas, and even within counties.

Chetty and Hendren [2018] exploit variation in the timing of children's moves across areas to identify a causal exposure effect of living in a particular neighborhood. They find that moving to a commuting zone where the mean income rank of the children of permanent residents is one percentile higher increases a child's income rank in adulthood by 0.04 percentiles, suggesting that place has a substantial childhood exposure effect. Furthermore, they find that the majority of the observed variation in outcomes across areas is due to causal effects of place.

3 Model

In this section we will develop a theoretical model that will complement the results presented in the remainder of the paper. In so doing, we hope to provide theoretical content to the assumptions made in the empirical sections, elucidating, in particular, the functional relationship between concentration in the provision of public goods and the character (read stringency) of land-use regulations. In brief, our object is to perform a comparative statics, analyzing the effect of an exogenous change in jurisdictional concentration on land-use regulations.

Preliminaries

Define a metropolitan area $M \equiv \{x \mid x \in \mathbb{R}^2,\ ||x|| \leq R\}$. The metropolitan area is comprised of jurisdictions $j \in \{0, ..., J\}$ with exogenously determined boundaries $[j_-, j_+] \in \mathbb{R}^2$ such that $j_+ > j_- \ \forall\ j$, $\cap_{j=0}^{J} \pi(j_+^2 - j_-^2) \backslash \{0_-, ..., J_+\} = \phi$, and $\cup_{j=0}^{J} \pi(j_+^2 - j_-^2) = \pi R^2$. We require that $0_- = 0$ and $J_+ = R$. Furthermore, locations are only heterogenous in their 'inherent' desirability to a prospective resident. Jurisdictions are indexed in reference to this 'inherent' desirability such that the first jurisdiction resides controls, in aggregate, the most desirable land, i.e. $\int_{0_-}^{0_+} \int_0^{2\pi} u(r,\theta) r d\theta dr > ... > \int_{J_-}^{J_+} \int_0^{2\pi} u(r,\theta) r d\theta dr$ where $u(r,\theta)$ is the 'inherent' utility conferred upon a household of residing at a particular location. Further, we require this quantity to decay with distance, or $\frac{\partial u(r)}{\partial r} < 0$.

The Consumer's Problem

$N \in \mathbb{N}$ consumers reside in the metropolitan area. Individuals are endowed with an income, $I_i \in \{H, L\}$ where $H > L$. The constraints placed on their actions are enumerated below.

1. *Budget Balance:* $I_i = Q_i + \int_0^{2\pi} \int_{j_-}^{j_+} \rho(r,\theta) h_i^d(r,\theta) r dr d\theta$

2. *Minimum Consumption:* $H_i^d \geq \beta_j \ \forall\ i \in \{0, ..., N_j\}$

Here, $I_i \in \{H, L\}$ is the consumer's income, Q_i is the non-housing good and the numéraire, $\rho(r,\theta) \in \mathbb{R}_+$ is the rent at location (r,θ), $h_i^d(r,\theta)$ is consumer i's housing consumption at a particular location, $H_i = \int_0^{2\pi} \int_{j_-}^{j_+} h_i^d(r,\theta) r dr d\theta$ is the consumer's total housing consumption, and $\beta_j \in \mathbb{R}_+$ is a policy set by the government that requires amount of housing be consumed. Implicitly, there is a third constraint.

3. *Residency:* $H_i^d(j) = 0 \; \forall \; j \neq j^*$

This simply states that consumer cannot distribute their housing consumption over various municipalities. Now lets, define the consumer's objective.

$$U_i = (Q_i)^{\xi_i^H} (H_i^d)^{1-\xi_i^H} \exp[\xi_i^u \int_0^{2\pi} \int_{j-}^{j+} u(r,\theta) \mathbb{1}\{h_i^d(r,\theta) > 0\}) r dr d\theta + \xi_i^T (\frac{T_j}{N_j})]$$

Here, $\xi_i^x \forall \; x \in \{H, u, T\}$ is a stochastic weight, idiosyncratic to the consumer, where $\xi_i^x \sim$ Lognormal$(0, \sigma^x)$ and $\xi_i^H \sim$ Beta(α^H, α^H). $T_j = \int_0^{2\pi} \int_{j-}^{j+} \gamma_j \rho(r,\theta) r dr d\theta$ is the revenue collected for the public good provided by the municipality, γ is a tax on rents collected by the government to fund its services, and N_j is the number of inhabitants in the municipality. The consumer's problem is to maximize U_i subject to the constraints, i.e.

$$j^*, h_i^{d*}(r,\theta) = \arg \max_{j, h_i^d(r,\theta)} U_i \text{ subject to 1-3}$$

or choose a jurisdiction and a housing consumption function for that jurisdiction.

The Developer's Problem

The developer is a price-taker, whose objective is to maximize profits,

$$\max \Pi = \max[\sum_{j=0}^{J} \int_{j-}^{j+} \int_0^{2\pi} (1-\gamma_j)\rho(r,\theta) h_i^s(K, L, r, \theta) - c(K, L, r, \theta, j) r d\theta dr]$$

subject to a single constraint

1. *Maximum Development:* $\int_{j-}^{j+} \int_0^{2\pi} h_i^s(K, L, r, \theta) r d\theta dr = H_j^s \leq \alpha_j$

Here, $h_i^s(K, L, r, \theta)$ is the housing supply function (taking as an input capital K and land L), and $c(\cdot)$ is the cost function. For the sake of simplifying exposition, suppose the cost function is linear in land and capital, i.e. $c(r, \theta, h_i^s, j) = \lambda(r, \theta)L(r, \theta) + (\tau_j + k)K(r, \theta)$, where $\lambda(r, \theta)$ is the cost of land and k is the cost of capital. τ is a policy set by the government that raises the cost of development. Employing a simplifying assumption, suppose the developer's production function is Cobb-Douglas, i.e. $h_i^s(r, \theta) = K(r, \theta)^d L(r, \theta)^{1-d}$ for some $d \in (0, 1)$. The developer's problem then becomes

$$\max \Pi = \max[\sum_{j=0}^{J} \int_{j-}^{j+} \int_{0}^{2\pi} (1-\gamma_j)\rho(r, \theta)K(r, \theta)^d L(r, \theta)^{1-d} - \lambda(r, \theta)L(r, \theta) - (\tau_j + k)K(r, \theta) r d\theta dr]$$

The developer will choose a capital expenditure function and land expenditure function that maximizes the expression, i.e.

$$K^*(r, \theta), L^*(r, \theta) = \arg\max \Pi$$

The Government's Problem

Jurisdictions will set a policy vector $\theta_j = \{\alpha, \beta, \tau, \gamma\}$ where $\theta_j \in \Theta \subseteq \mathbb{R}_+^3 \times [0, 1]$. Here, α is a density restriction, β is a minimum consumption requirement, τ is a 'regulatory tax' (i.e. a policy that does not generate revenue, and makes development more expensive, but does not interdict it), and γ is a tax collected on rents.

The government's problem is to maximize its objective function, or

$$\max_{\theta \in \Theta} \Psi = \max_{\theta \in \Theta}[\iota \sum_{i=1}^{N_j} U_i + (1 - \iota)(\Pi + 1)]$$

where ι is a function that describes the relative influence of residents (as opposed to industry lobbies) over their local government. We require that $\frac{d\iota}{dN_j} > 0$, that is to say the influence of residents be increasing in the number of consumers in the jurisdiction. In order to simplify exposition, let's assume that $\iota \equiv \exp(-\exp(r - v\frac{\sum_{i=1}^{N_j} I_i}{\Pi+1}))$ where $v, r \in \mathbb{R}_+$.

This formulation inscribes two assumptions about the functioning of local governance:

1. Residents with higher incomes are more effective at lobbying their government, either because they have the means to do so, or simply because local politicking is 'normal.'
2. Jurisdictions with fewer residents are more responsive to the desires of developers. This follows from an assumption that as developers operate in the entire urbanized area, they have more resources than the combination of households in one jurisdiction. As a result, developers *a priori* achieve the minimum 'effective scale of political participation.'

Characterization of Equilibrium

Our object then is to analyze the elasticity of a city's land-use regulations with respect to the concentration of 'desirable land', formally $\frac{\partial\bar{\alpha}}{\partial g}, \frac{\partial\bar{\beta}}{\partial g}, \frac{\partial\bar{\tau}}{\partial g}$ where

$$\bar{x} \equiv \int_0^R \int_0^{2\pi} x(r,\theta)\frac{u(r,\theta)}{\int_0^R \int_0^{2\pi} u(r,\theta) r d\theta dr} r d\theta dr \ \forall\ x \in \{\alpha, \beta, \gamma\}$$

and where g, the Gini Coefficient, is

$$g \equiv \sum_{j=1}^{J} \frac{1}{2}(\frac{j}{J} + \frac{j-1}{J}) * (\frac{j}{J} - \frac{j-1}{J}) - (\frac{\sum_{i=0}^{j-1} \int_{i-}^{i+} \int_0^{2\pi} u(r,\theta) r d\theta dr}{\int_0^R \int_0^{2\pi} u(r,\theta) r d\theta dr}) * (\frac{j}{J} - \frac{j-1}{J})$$

where jurisdictions are indexed in ascending order by $u(r)$.

To simplify exposition, we will make some several assumptions before proceeding.

1. $\int_0^R \int_0^{2\pi} u(r) r d\theta dr = 1$

2. $u(r) \equiv R - r$

3. $\rho(r,\theta) \equiv p_j r + s_{j(r,\theta)}$ where $p_j \in \mathbb{R}, s_j \in \mathbb{R}_+,\ p_j j_+ + s_j \geq 0$

4. $\lambda(r,\theta) \equiv -r + q_{j(r,\theta)}$ where $q_j \in \mathbb{R}_+,\ q_j \geq j_+$

5. $K(r,\theta) \equiv K_{j(r,\theta)}$ where $K_j \in \mathbb{R}_+$

1) and 2) readily imply

$$\int_0^R \int_0^{2\pi} (R-r) r d\theta dr = 1 \implies R = (\frac{3}{\pi})^{\frac{1}{3}}$$

As housing supply meets housing demand in equilibrium, i.e. $h_i^s(r,\theta) = h_i^d(r,\theta)\ \forall\ (r,\theta) \in [0,R] \times [0,2\pi]$, we will proceed by re-defining housing demand as

6. $h_i^d(r,\theta) \equiv K^d_{j(r,\theta)}(\mathbb{1}[b_i < r < c_i])^{1-d}$ where $\exists\ j^* \mid j^*_- \leq b_i < c_i \leq j^*_i$

The housing consumption equilibrium condition and 6) readily imply

$$(\bigcap_{i=1}^{N}(b_i,c_i) = \phi) \wedge (\bigcup_{i=1}^{N}[b_i,c_i] = \pi(\frac{3}{\pi})^{\frac{2}{3}} \sum_{j=0}^{J} K_j^d)$$

As land supply meets land demand in equilibrium, i.e. $L(r,\theta) = 1\ \forall\ (r,\theta)$, it follows that

$$L_j = \int_{j_-}^{j_+} \int_0^{2\pi} 1 * r d\theta dr = \pi \Delta^2 j_+\ \forall\ j$$

where $\Delta^x n = n^x_+ - n^x_-$,

Using the above, we can write the developer's objective function as

$$\Pi = 2\pi \sum_{j=0}^{J} (1-\gamma_j)(\frac{p_j \Delta^3 j_+}{3} + \frac{s_j \Delta^2 j_+}{2})K_j^d - \frac{\Delta^2 j_+}{2}(k+\tau_j)K_j + \frac{\Delta^3 j_+}{3} - q_j \frac{\Delta^2 j_+}{2}$$

Solving the first order conditions with respect to K_j, we can find the optimal capital expenditure for each jurisdiction given the constraint imposed on development. It follows that the optimal capital expenditure for each jurisdiction is

$$K_j^*(p_j,s_j)=\begin{cases}0 & \frac{p_j\Delta^3 j_+}{3}+\frac{s_j\Delta^2 j_+}{2}\leq 0\\ \left(\frac{\frac{\Delta^2 j_+}{2}(k+\tau_j)}{d(1-\gamma_j)(\frac{p_j\Delta^3 j_+}{3}+\frac{s_j\Delta^2 j_+}{2})}\right)^{\frac{1}{d-1}} & 0<\frac{p_j\Delta^3 j_+}{3}+\frac{s_j\Delta^2 j_+}{2}\leq\frac{\frac{\Delta^2 j_+}{2}(k+\tau_j)}{(\frac{\alpha_j}{\pi\Delta^2 j_+})^{\frac{d-1}{d}}d(1-\gamma_j)}\\ (\frac{\alpha_j}{\pi\Delta^2 j_+})^{\frac{1}{d}} & \frac{\frac{\Delta^2 j_+}{2}(k+\tau_j)}{(\frac{\alpha_j}{\pi\Delta^2 j_+})^{\frac{d-1}{d}}d(1-\gamma_j)}<\frac{p_j\Delta^3 j_+}{3}+\frac{s_j\Delta^2 j_+}{2}\end{cases}$$

Supposing that developers make zero profits in the absence of binding supply constraints (given free entry and exit) we can recover the price for land.

$$(*)\ q_j=\begin{cases}\frac{2\Delta^3 j_+}{3\Delta^2 j_+}\\ \frac{2(1-\gamma_j)}{\Delta^2 j_+}(\frac{p_j\Delta^3 j_+}{3}+\frac{s_j\Delta^2 j_+}{2})K_j^d-(k+\tau_j)K_j+\frac{2\Delta^3 j_+}{3\Delta^2 j_+}\\ \frac{K_j^d(k+\tau_j)}{d(\frac{\alpha_j}{\pi\Delta^2 j_+})^{\frac{d-1}{d}}}-(k+\tau_j)K_j+\frac{2\Delta^3 j_+}{3\Delta^2 j_+}\end{cases}$$

where the conditions are the same as for the optimal capital expenditure function. It follows that we can write the developers profits as

$$\Pi=2\pi\sum_{j=0}^{J}(1-\gamma_j)(\frac{p_j\Delta^3 j_+}{3}+\frac{s_j\Delta^2 j_+}{2})K_j^{*d}-\frac{\Delta^2 j_+}{2}(k+\tau_j)K_j^*+\frac{\Delta^3 j_+}{3}-(*)\frac{\Delta^2 j_+}{2})$$

Using the budget balance condition and the above, we can rewrite the consumer's objective

$$U_i=[I_i-2\pi K_j^d(\frac{p_j\Delta^3 c_i}{3}+\frac{s_j\Delta^2 c_i}{2})]^{\xi_i^H}[K_j^d\pi\Delta^2 c_i]^{1-\xi_i^H}\exp[\xi_i^u(\frac{(\frac{3}{\pi})^{\frac{1}{3}}\Delta^2 c_i}{2}-\frac{\Delta^3 c_i}{3})+\xi_i^T(\frac{2\pi\gamma_j(\frac{p_j\Delta^3 j_+}{3}+\frac{s_j\Delta^2 j_+}{2})}{N_j}]$$

The consumer has several constraints on their housing choices within the city, enumerated here:

1. *Tractability Constraints:* $-c_i \leq 0$, $-b_i \leq 0$, $-c_i + b_i \leq 0$

2. *Minimum Consumption:* $-c_i^2 + b_i^2 - \frac{\beta_j}{K_j^d \pi} \leq 0$

3. *Residency:* $\exists\ j \mid (j_- \leq \frac{c_i+b_i}{2} \leq j_+) \wedge (c_i \leq j_+) \wedge (j_- \leq b_i)$

4. *Market Clearing:*

   (a) $(\exists\ -i \neq i \mid c_i - b_{-i} = 0)\ \oplus\ (c_i = (\frac{3}{\pi})^{\frac{1}{3}})$

   (b) $(\exists\ -i \neq i \mid b_i - c_{-i} = 0)\ \oplus\ (b_i = 0)$

Lastly, the consumer can take the 'outside option', i.e. choose to reside outside the city:

5. *Outside Resident:* $(R \leq \frac{c_i+b_i}{2}) \wedge (c_i = b_i) \wedge (N_j = 1) \wedge (H_i^d = C_i) \wedge (j_+ = j_-)$

As demand behavior is invariant to positive monotone transformations of the utility function, we will take the natural log of the expression, and substitute in indicator functions into the expression to make the choice over jurisdictions tractable.

$$
\begin{aligned}
(*)\ & \xi_i^H \ln[I_i - 2\pi(\sum_{j=0}^{J} \mathbb{1}[j_- \leq \frac{c_i+b_i}{2} \leq j_+] K_j^d (\frac{p_j \Delta^3 c_i}{3} + \frac{s_j \Delta^2 c_i}{2}))] \\
& + (1-\xi_i^H) \ln[(\sum_{j=0}^{J} \mathbb{1}[j_- \leq \frac{c_i+b_i}{2} \leq j_+] K_j^d) \pi \Delta^2 c_i + \mathbb{1}[\frac{c_i+b_i}{2} \geq R] * C_i] + \xi_i^u \left(\frac{(\frac{3}{\pi})^{\frac{1}{3}} \Delta^2 c_i}{2} - \frac{\Delta^3 c_i}{3} \right) \\
& + \xi_i^T \left(\frac{2\pi(\sum_{j=0}^{J} \mathbb{1}[j_- \leq \frac{c_i+b_i}{2} \leq j_+] \gamma_j (\frac{p_j \Delta^3 j_+}{3} + \frac{s_j \Delta^2 j_+}{2}))}{\mathbb{1}[\frac{c_i+b_i}{2} \geq (\frac{3}{\pi})^{\frac{1}{3}}] + \sum_{j=0}^{J} \mathbb{1}[j_- \leq \frac{c_i+b_i}{2} \leq j_+] (\sum_{i'=1}^{N} \mathbb{1}[j_- \leq \frac{c_{i'}+b_{i'}}{2} \leq j_+])} \right)
\end{aligned}
$$

Before we characterize the solution we will introduce another constraint on the consumer's problem which will allow us to recover the rental price.

6. *Rent Capitalization:*

$$\bar{U} = \xi_i^H \ln[1 - \frac{2\pi}{I_i}(\sum_{j=0}^{J} \mathbb{1}[j_- \leq \frac{c_i + b_i}{2} \leq j_+] K_j^d (\frac{p_j \Delta^3 c_i}{3} + \frac{s_j \Delta^2 c_i}{2}))]$$
$$+ (1 - \xi_i^H) \ln[(\sum_{j=0}^{J} \mathbb{1}[j_- \leq \frac{c_i + b_i}{2} \leq j_+] K_j^d) \pi \Delta^2 c_i + \mathbb{1}[\frac{c_i + b_i}{2} \geq R] \exp(\frac{\bar{U}}{(1 - \xi_i^H)})]$$

which simply states that consumers are indifferent between their housing bundle and that of everyone else. Breaking this down, we can see that the disutility of an increase in spending on housing is represented by a decline in the share of income spent on the non-housing good, while the utility of housing spending is made manifest by increased consumption of the housing good. This assumption can also be stated as the assumption that the utility conferred upon a consumer from consuming housing is capitalized in rents, while the 'inherent utility' and the utility of the public good is not fully capitalized in rents.

Using this condition, we can rewrite the objective function as

$$(**)\ \xi_i^H \ln[I_i] + \bar{U} + \xi_i^u \left(\frac{(\frac{3}{\pi})^{\frac{1}{3}} \Delta^2 c_i}{2} - \frac{\Delta^3 c_i}{3} \right)$$
$$+ \xi_i^T \left(\frac{2\pi(\sum_{j=0}^{J} \mathbb{1}[j_- \leq \frac{c_i+b_i}{2} \leq j_+] \gamma_j (\frac{p_j \Delta^3 j_+}{3} + \frac{s_j \Delta^2 j_+}{2}))}{\mathbb{1}[\frac{c_i+b_i}{2} \geq (\frac{3}{\pi})^{\frac{1}{3}}] + \sum_{j=0}^{J} \mathbb{1}[j_- \leq \frac{c_i+b_i}{2} \leq j_+](\sum_{i'=1}^{N} \mathbb{1}[j_- \leq \frac{c_{i'}+b_{i'}}{2} \leq j_+])} \right)$$

While there are invariably countless ways we could represent the process by which consumers 'sort', that is to say simultaneously arrive at some spatial equilibria given competing priorities and conflicting interests, we will imagine this to be a coordinated process, by which a 'central planner' maximizes the sum of utilities, arriving at some local optimum. While this is not a particularly principled stand, it is motivated by expediency and the intractatbility of the problem (computationally) under an alternative mode of finding a solution. In this way, a sort is characterized by

$$\{(c_i^*, b_i^*)\}_{i=1}^N = \arg\max_{\{(c_i,b_i)\}_{i=1}^N} \sum_{i=1}^N (**)$$

subject to

1. *Tractability Constraints:* $(-c_i \leq 0) \wedge (-b_i \leq 0) \wedge (-c_i + b_i \leq 0) \; \forall \; i$

2. *Market Clearing:* $\mathbb{1}[\frac{c_i+b_i}{2} \leq (\frac{3}{\pi})^{\frac{1}{3}}][b_i \prod_{i' \neq i}(b_i - c_{i'}) + (c_i - (\frac{3}{\pi})^{\frac{1}{3}}) \prod_{i' \neq i}(c_i - b_{i'})] = 0$

3. *Residency:* $\sum_{i=0}^J \mathbb{1}[j_- \leq \frac{c_i+b_i}{2} \leq j_+]((c_i - j_+) + (j_- - b_i)) \leq 0 \; \forall \; i$

4. *Minimum Consumption:* $\sum_{i=0}^J \mathbb{1}[j_- \leq \frac{c_i+b_i}{2} \leq j_+](-c_i^2 + b_i^2 - \frac{\beta_j}{K_j^d \pi}) \leq 0 \; \forall \; i$

5. *Tractability of Rents:* $(s_j \geq 0) \wedge (p_j j_+ + s_j \geq 0) \; \forall \; j$

6. *Rent Capitalization*

Given a 'sorting' function (that is to say a full understanding of how consumer's will 'sort' given a particular setting of exogenous parameters and policy vectors), government's will maximize their payoff functions, implementing a policy θ_j^* such that

$$\Psi_j(\theta_j^*, \theta_{-j}^*) \geq \Psi_j(\theta_j, \theta_{-j}^*) \; \forall \; \theta_j \in \Theta$$

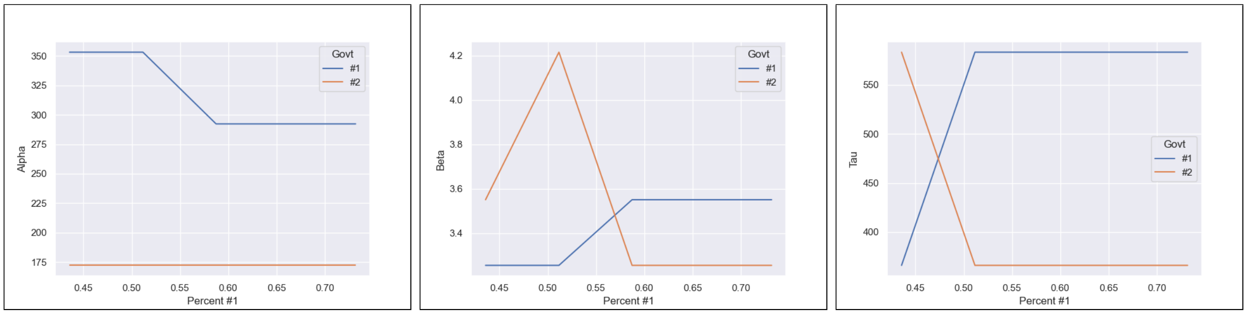
i.e. the Nash equilibrium strategy. While the existence of a pure strategy Nash equilibrium in infinite strategic form games is well known given certain regularity conditions on the payoff function (see *Debreu, Glicksberg, and Fan*), identifying this equilibrium is computationally difficult in the context of a numerical simulation with this particular model. As a result, we will admit some mixture over a set of discrete pure strategies which will assure the existence of a Nash equilibrium in a finite strategic form game.

Numerical Analysis

As has been alluded to previously, characterizing a 'sort' and then allowing governments to compete over this 'sorting' function is difficult. For one, the 'sorting' function does not admit a closed-form solution, which preempts all modes of analysis except for numerical computations. Furthermore, the consumer's objective (given constraints) is highly discontinuous. As a result, all off-the-shelf optimization algorithms (known to the author at least) fail to reach a solution. Consequently, we implement our own optimization routine which, in principle, arrives at a local maximum to the consumer's problem. In brief, we permute across all possible configurations of $\{c_i, b_i\}_{i=1}^{N}$ for which the market clearing condition holds and consumers within the same jurisdiction consume the same amount of housing, choosing that arrangement which minimizes the absolute deviations from the rent capitalization constraint (i.e. is not dominated in this measure by any other arrangement). We then optimize the consumer's objective for each jurisdiction subject to the enumerated constraints, arriving at a local optimum. We run this process this for one particular setting of the exogenous parameters (in particular, where $N = 5$ and $J = 2$), for several settings of the boundary between jurisdictions 1 and 2 (which, mechanically, determines concentration in the 'inherent desirability' of land), and over the Cartesian product of the permutations of a discrete set of well-chosen policy vectors.

In all, we computed over 4,000 solutions, a process that took well over 24 hours. Given these solutions (a vector of endogenous variables), we computed each government's payoff given the policy they implemented, and the policy that their opponent (the other government) implemented. We then arranged these payoffs into a 2x2 matrix, producing one matrix per boundary setting. Using the Lemke-Howson algorithm, we computed the Nash equilibria for each setting of the boundary, discarding equilibria that saw the players implement a mixed strategy. We then compared the payoffs under each equilibria, choosing that equilibria which dominated the others (i.e. where payoffs were higher for both governments). This procedure eliminated all equilibria except for one for each setting of the boundary.

The final results of this procedure are presented here.

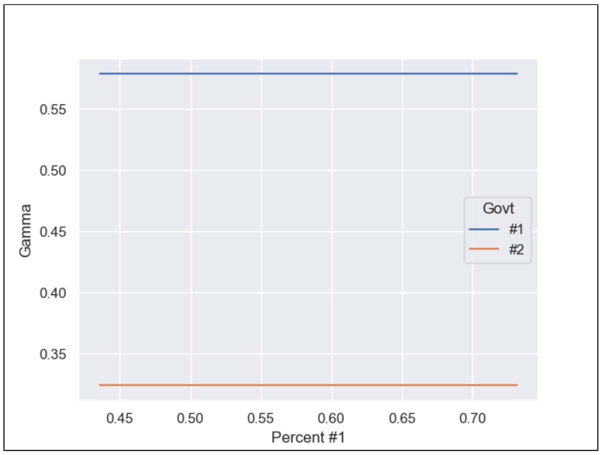


α β τ

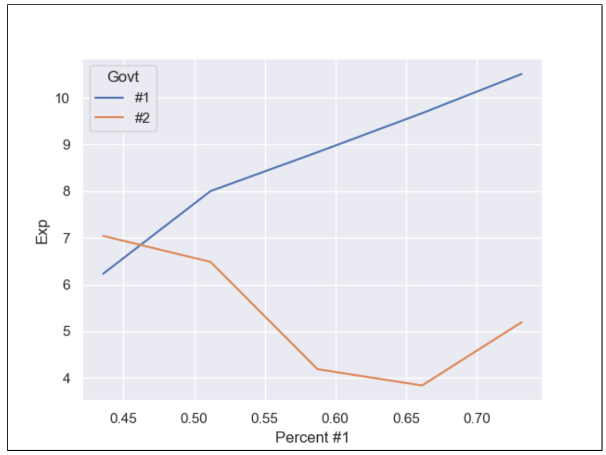
Implemented Regulations by Government

On the y-axis, we have the value of the implemented regulation, while on the x-axis we have the percentage of land (weighted by its 'inherent desirability') in the city under government #1's jurisdiction (i.e. the government closest to the origin). Starting with α, our cap on intensive development, we see that it is weakly declining for government #1 throughout the range (i.e. becomes stricter), while it remains constant (albeit, at a lower value) for government #2. This would suggest that α is weakly decreasing in concentration for all governments. With β, we do not observe this monotonic property. This regulation — which prescribes a minimum level of housing consumption — is weakly rising in concentration for government #1, but is falling (on the whole) in concentration for government #2. Lastly, τ, the 'regulatory tax' exhibits much the same pattern as β, rising in concentration for government #1 and falling in this same quantity for government #2. This would suggest that the government that controls a majority of the city's 'desirable', regardless of its geographic location, has an incentive to implement the most stringent regulations.

We now present our findings on government finances, i.e. optimal taxation and expenditure policies.



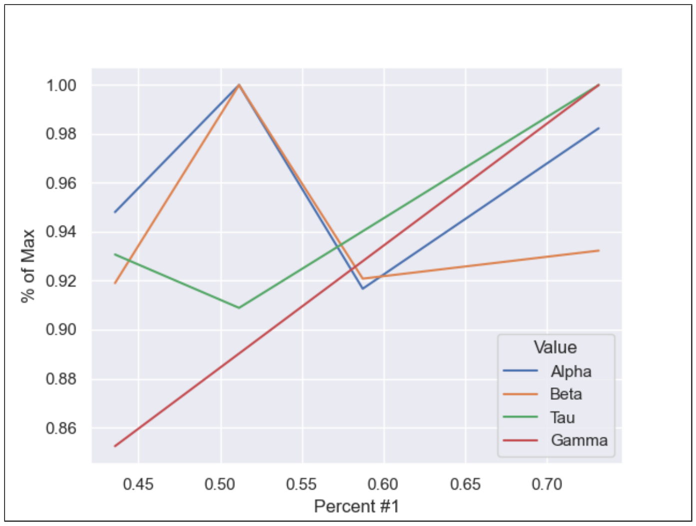
γ



Expenditures per Capita

Government Finances

Evidently, the optimal tax policy is independent of concentration in land. This is because there is strong sorting on income, with government #1 being uniformly comprised of high income households and government #2 uniformly being comprised of low-income households. By introducing further heterogeneity in the incomes of individuals or by allowing for more jurisdictions, we might yet see some dependence of the optimal tax policy on land concentration. While the optimal tax rate is invariant, expenditures per capita seem to rise in concentration for government #1, and fall in this same measure for government #2. This would suggest that individuals are pushed out of government #1 and towards government #2 while concentration increases, a result of more stringent land-use regulations in the former. Lastly, we will examine a particular statistic of the regulations: regulations weighted by the percentage of 'desirable land' controlled by the jurisdiction and normalized to one (to allow for easy comparison).



Regulations, Normalized and Weighted by Percent of Land Control

Starting with $\bar{\gamma}$, we see that it increases monotonically in concentration. This result is mechanical. Even though γ is constant for both governments throughout the range, this is a result of simply apportioning more land to the higher tax jurisdiction. Similarly, $\bar{\alpha}$ is rising on some portions of the range, even though α is weakly falling for both governments. With respect to $\bar{\beta}$ and $\bar{\tau}$ we observe them following much the same pattern as $\bar{\alpha}$ and $\bar{\gamma}$ respectively.

While these findings suffer from numerical instability (a result of performing a relatively small number of function evaluations), we can derive certain testable implications from these. For one, this model would suggest that governments controlling a majority of 'desirable land', regardless of their geographic location, possess an incentive to implement stricter regulations. Furthermore, we observe that communities sort on income in the presence of land-use regulations. Though the contrapositive has not been shown, the divergence is nevertheless striking. Lastly, the regulatory statistics bear some functional relationship to the level of concentration, even if it is a mechanical one.

In future work, we hope to expand on this model. Preliminarily, with greater computational power, we could evaluate the function various settings of the policy vectors and exogenous paramaters, and in so doing compute elasticities of the endogenous variables in the exogenous. Secondarily, the question of the competing interests of households and developers remains underdeveloped. Of particular interest is the question of when the interests of households and developers are at odds — which would require government's to resolve conflicting interests — and when they are in lockstep, pushing either for more or less regulation.

4 Data

This section discusses the data used in the writing of this paper, specifically their sources, and the means by which they were processed to produce inputs for our statistical models.

To open the discussion, there were four main sources of data:

1. **Text:** 22,963 legal codes representing 2,612 unique municipal and county governments over 23 years.

2. **GIS:** The perimeter, area, and shape of undevelopable areas within the urban growth boundary in 2010, derived from United States Geological Survey land use and public lands data.

3. **Census:** Demographic and economic characteristics of various geographies, ranging from Census Blocks to counties from the 1990 and 2010 Decennial Censuses, as well as the 2006-2010 American Community Survey.

4. **Opportunity Atlas:** Average income in 2015 of adults born between 1978 and 1983 (modally, 35 years of age) by Census tract in which they grew up (Chetty et al. [2018]).

We will now discuss each in turn in some more depth to build an understanding of the potential uses of the data and their limitations.

Text

Text data was sourced from Municode, a codifier of legal documents for local governments in the United States. Municode's website suggests that the company services over 4,200 municipal governments and has been in operation since 1951 (Municode About Us). A subset of published codes are available through their online library (Municode Library). Using Selenium, an open source Python package used to automate web browser interactions, we scraped all codes available through this portal (both past and present). In all, these were 22,963, representing 2,612 unique municipal and county governments. While several observations were available for 1989 (the minimum year), coverage is mostly limited to the latter half of the 2010's, with 2017 being the first year in which a code exists for close to a majority of jurisdictions in the sample which were in urban areas in 1990 (48% to be precise). While a plurality of urbanized jurisdictions only have one year available (23%), the vast majority of urbanized jurisdictions are represented in 3 or more years (70.8%).

Municipal codes are voluminous, containing regulations on all aspects of municipal governance, including sanitation, public safety, healthcare, and sewage. In order to extract the portions of the code that were germane to land use we used a natural language processing model closely related to that of Devlin et al. [2018] called S-BERT, which allows for faster computations of sentence-length embeddings (Reimers and Gurevych [2019]).[3] In brief, we use a model pretrained on a large corpus of natural language (including text from, *inter alia*, Wikipedia, Yahoo Answers, and Stack Exchange), embed chapter and section headings (i.e. assign them a vectorial representation), and calculate the cosine similarity between these and the embeddings of a list of search terms, picking those chapter and sections that are

[3]For a more extensive discussion of this technology, please refer to the following MIT Press Primer, which presents an introduction to the model for the uninitiated.

semantically similar to our target. Formally,

$$\min_{s \in S} \left\{ \frac{f(i) \cdot f(s)}{||f(i)||||f(s)||} \right\} \leq T \in [0, 1]$$

where $f(\cdot)$ is our sentence model, i is our chapter or section heading, and s is our search term, and T is our threshold. Our list of search terms was comprised of words and phrases related to construction, development, and land use (e.g. "architectural", "growth areas", and "property maintenance"). After iterating through different combinations of these, a final list of 17 phrases was compiled which retrieved the most comprehensive and cogent set of chapters. We then fine-tuned the pre-trained model, giving it a hand-made list of entries which were incorrectly admitted. The fine-tuned model was then run over the entire corpus of legal codes, returning a selection of chapters for each code that cleared the threshold.

land-use regulations were then converted into a term-frequency inverse document frequency matrix (TF-IDF) matrix. Formally, suppose that each document $d \in \{1, .., D\}$ in the corpus, $\mathcal{C}$, is summarized as a count of each term $t \in \{1, .., T\}$ (in our case, 3-grams, or continuous sequences of three words or less) where the count is denoted by $f_{t,d}$. Then, the entry (t, d) of our TF-IDF matrix, Γ, is defined as

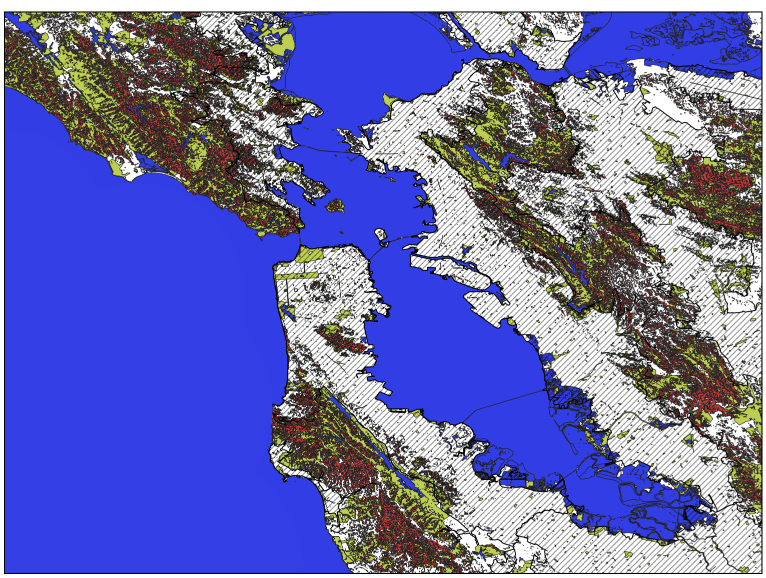
$$\Gamma_{t,d} \equiv \frac{f_{t,d}}{\sum_{t' \in \{1,..,T\}} f_{t',d}} \frac{D}{\sum_{d' \in \{1,..,D\}} \mathbb{1}[f_{t,d'} \neq 0]}$$

This statistic is robust to common, but economically meaningless words (think 'and', 'but', 'the'), instead, giving greater weight to 'salient' words that are common in a particular text, but uncommon in the corpus at large.

GIS

Data on undevelopable land in urbanized areas was obtained from the United States Geological Survey. Following the relevant literature (including Saiz [2010]), land was said to be undevelopable if it either belonged to a public entity (say, the federal government), consisted of open water or wetlands (either undevelopable by definition, or protected by state and federal laws), or resided on a surface with a slope of more than 20 degrees (which is generally considered to be an unsuitable grade for development). Data for these was taken from the 2010 Protected Areas Database (PAD-US), the 2011 National Land Cover Database (NLCD), and from the Gap Analysis Project (GAP), respectively. Lastly, GIS data for 2010 urbanized areas was courtesy of IPUMS NHGIS (Manson et al. [2021]).

After cleaning, pre-processing, and concatenation, undevelopable areas were 'differenced' from urbanized areas (i.e. portions of the urbanized area that intersected with undevelopable areas were discarded), yielding the shape and location of *developable* urbanized areas. Below, we include a representative image of an urbanized area with undevelopable areas overlain.



San Francisco Urbanized Area in 2010

(Water and Wetlands ● ; Slope $>$ 20 Degrees ● ; Public Lands ●)

We also used GIS data to compute a measure of jurisdictional atomization, that is to say the degree to which developable areas in a city were fragmented among different localities. This measure was an adaptation of the canonical Gini coefficient, defined below.

Definition (Gini): The Gini coefficient, g, for each city is given by

$$g_c \equiv \sum_{j=1}^{J_c} \frac{1}{2}(\frac{j}{J} + \frac{j-1}{J}) * (\frac{j}{J} - \frac{j-1}{J}) - (\frac{\sum_{i=0}^{j-1} u_i}{\sum_{i=0}^{J_c} u_i}) * (\frac{j}{J} - \frac{j-1}{J})$$

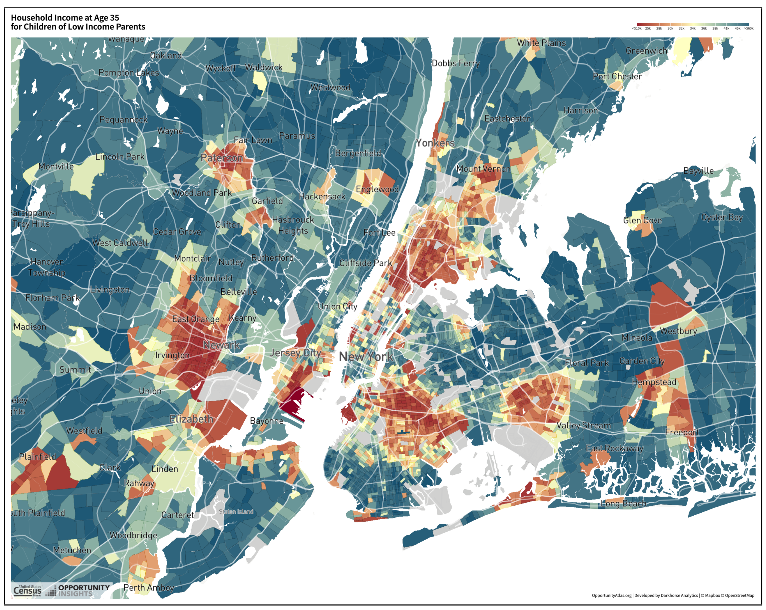
where, $u_j \equiv \sum_{t=1}^{T_j}[(\max_{t' \in T_c} \mathbb{E}_{S_n}[c_{t'}]) - \mathbb{E}_{S_n}[c_t]] * a_t$; $\mathbb{E}_{S_n}[c_t]$ is the sample mean commute time for the tract; and a_t is the area of the tract. Furthermore we require that jurisdictions be indexed in ascending order by u_j, such that $u_{J_c} > u_{J_c - 1} > ... > u_0$. In so doing, we obtain a measure of how unequal the distribution of prime land is among jurisdictions (that is to say land that has a relatively low commute time). Further, $g \in [0, \frac{1}{2}]$, with $\frac{1}{2}$ representing a situation where a single municipality's jurisdiction encompasses the urbanized area.

To calculate this, we first obtained GIS data for municipalities and counties in 2010 from IPUMS NHGIS. We then 'differenced' counties and municipalities, obtaining a set of county areas not in municipalities. As counties encompass municipalities, this was done in order to uniquely assign area to a jurisdiction. We then 'differenced' these and municipalities with developable urbanized areas, obtaining a set of developable, urbanized, jurisdictions. Lastly, we calculated u_j for each jurisdiction using a weighted sum of sample mean commute times at the tract level (weighted by developable area of tract), also from IPUMS NHGIS.

Census

Economic and demographic for 1990 and 2010 Census Tracts was obtained from IPUMS NHGIS. These were in turn, derived from the 1990 and 2010 decennial Censuses and from the 2006-2010 American Community Survey. In most cases, data was collected for a smaller geography (Census Blocks for 1990, and Census Block Groups for 2010) and aggregated to the tract level by population weighting (where appropriate) to avoid dropping tracts with missing or incomplete data. Summary statistics for Census Tracts in the 2010 regression sample are provided in the appendix (C.1). Similarly, covariates for jurisdictions (counties and municipalities) were constructed by taking a weighted average of tract covariates where appropriate. This was done first for municipalities, and second for counties, such that all tracts not in a municipality in urbanized areas were assigned to counties.

Opportunity Atlas



Income at Age 35 of Children with Low Income Parents

Data on later-in-life outcomes was taken from the Opportunity Atlas (Chetty et al. [2018]). These include the mean predicted household income of an adult born between 1978 and 1983 for the Census Tract in which they grew up. Outcomes are provided as a tract-average (pooled), and conditional on parental income (by income quartile, namely the 25th, the 50th, and 75th percentiles of the household income distribution in 1990). These outcomes were merged with the tract-level covariates (described above), as well as with the regulatory indices (described below).

5 Methodology

In this section we describe the methodological underpinnings of the paper. It is divided into four subsections: *concept recovery*, *citywide effective regulation*, *surrogate indices*, and *modelling*, a treatment of text, regulatory, Opportunity Atlas, and merged data respectively.

Concept Recovery

This subsection defines 'concepts' and describes the process of 'concept recovery'.

Definition (Concept): A concept, $\nu \in \mathbb{R}_+^D$, is such that $\nu = f(\Gamma)$ for some deterministic function $f : \mathbb{R}_+^{D \times T} \to \mathbb{R}_+^D$, i.e. maps a TF-IDF matrix to the reals. Further, outcomes $\omega \sim \mathcal{W}(\nu, \kappa)$ are observed for each document such that $\omega = \nu\kappa' + \epsilon$ where $\omega \in \mathbb{R}_+^{D \times K}$, $\kappa \in \mathbb{R}_{++}^K$, $\epsilon \in \mathbb{R}^{D \times K}$ and $\epsilon_d \sim \mathcal{D}$ where $\mathbb{E}_{\mathcal{D}}[\epsilon_d] = 0,\ \epsilon_d \perp\!\!\!\perp d$.

Our definition readily implies the following properties, which will aid in interpretation of our estimand, $\hat{\nu}$:

Properties:

1. *Outcomes are zero in expectation when* ν *is zero*: $\nu_d = 0 \implies \mathbb{E}_{\mathcal{D}}[\omega_d] = 0$
2. *Outcomes are increasing in* ν: $\frac{\partial \mathbb{E}_{\mathcal{D}}[\omega_d]}{\partial \nu_d} = [\frac{\partial \mathbb{E}_{\mathcal{D}}[\omega_{1,d}]}{\partial \nu_d}, \frac{\partial \mathbb{E}_{\mathcal{D}}[\omega_{2,d}]}{\partial \nu_d}, ..., \frac{\partial \mathbb{E}_{\mathcal{D}}[\omega_{K,d}]}{\partial \nu_d}] >> 0$
3. ν *is identified*: $\nexists\ \nu \neq \nu' \mid \mathcal{W}(v) = \mathcal{W}(v')$

A brief proof of this last property is provided in the appendix (B).

Further, suppose that our data is comprised of two samples, a paired sample P where we observe D_{P} tuples $(\omega_d, \Gamma_d) \in \{\mathbb{R}_+^K \times \mathbb{R}_+^T\}$ (i.e. text data and outcomes) and an unpaired sample U where we observe D_{U} elements of $\Gamma_d \in \mathbb{R}_+^T$.

Problem ('Concept Recovery'): Our objective in 'concept recovery' is to estimate $\hat{\nu_d} \; \forall \; d \in \{1, ..., D_{\text{P}} + D_{\text{U}}\}$.

Proposition: So long as $\mathbb{E}[\omega_{i'} \omega_i'] > 0 \; \forall \; i, i' \in \mathbb{R}^K$, we can consistently estimate the concept $\hat{\nu}$, i.e. $\lim_{D \to \infty} \mathbb{P}(||\hat{\nu} - \nu|| > \delta) = 0$.

The proof is left as an exercise for the reader. In all seriousness, while this result remains undemonstrated, we hope to expand on this in future work, proposing a suitable estimation routing. This process is analogous, if not identical to a *low-rank denoising* problem, which has been extensively studied, and admits various estimation procedures (e.g. McRae and Davenport [2021]).

In lieu of a more principled estimation routine, we will use an off-the-shelf neural network with a specified architecture. Namely, we require that the last hidden layer of the neural network have the following form

$$\max(0, \hat{\kappa} * \hat{v}) : \mathbb{R}_+ \to \mathbb{R}_+^K \mid \hat{\kappa} >> 0$$

i.e. that the last hidden layer have a single, real-valued node, that it have a rectified linear activation function, that the weights be strictly positive, and that it have no intercept or *bias* (in the parlance of the machine learning literature). Given these restriction on the model, our estimate of the concept will preserve all of the properties that we enumerated above.

With respect to the evaluation of land-use regulations, we posit that three concepts can be recovered from these documents: α, restrictions on intensive and extensive development, β, minimum housing consumption requirements, and τ, 'regulatory taxes' (i.e. regulations that do not interdict housing construction, but make the process less profitable by adding costs or increasing uncertainty arround approval).

Furthermore, we observe our TF-IDF matrix (refer to 4 to see how this was constructed) and outcomes, the responses to the survey questions used to construct the latest wave of the Wharton Residential Land Use Regulation Index from 2018 (Gyourko et al. [2021]). The answers to these survey questions were binned by the concept they corresponded to (refer to A for a list of questions and their corresponding bin). Values assigned to these questions were signed appropriately and normalized to the 0-1 range so that the neural network would not attempt to minimize mean squared error by favoring questions with arbitrarily higher values. For each bin the covariance matrix was calculated to assure nonnegatvity.

Three neural networks with three hidden layers each (20 nodes, 10 nodes, 1 node with the required form) were fitted on the tuple (Γ_d, ω_d) for all documents in 2018 for which we had survey responses. Given fitted models, we estimated α, β, and τ for all documents in our TF-IDF matrix for all years.

Similarly, we also fit a neural network with two hidden layers (20 nodes each), on the tuple $(\Gamma_d, \text{WRLURI}_d)$ for all documents in 2018 for which we had the index. Given this fitted model, we imputed the WRLURI for all documents and for all years.

We then calculated the covariance matrix of the estimated concepts and the synthetic WRLURI.

Table 5.1: Regulatory Indices Correlations

	WRLURI	α	β	τ
WRLURI	1.000	0.197	0.140	0.278
α	0.197	1.000	0.466	0.932
β	0.140	0.466	1.000	0.508
τ	0.278	0.932	0.508	1.000

All components of this matrix are positive, suggesting that jurisdictions that implemented one of these regulations to a high degree are more likely to do the same for the others. The highest correlation is between α and τ at .93. The lowest is between α and β at .47. Furthermore, the WRLURI is largely dissimilar from all three concepts, with the correlations between it and all concepts less than .2.

We then calculated the autocovariances of the regulations for all available lags.

Table 5.2: Regulatory Indices Autocorrelations

Lag	WRLURI	α	β	τ	Obs.
1	0.994	0.963	0.989	0.961	4090
2	0.989	0.950	0.983	0.949	3501
3	0.984	0.927	0.974	0.925	2854
4	0.979	0.910	0.973	0.908	2274
5	0.975	0.897	0.967	0.896	1793
6	0.974	0.902	0.972	0.898	1365
7	0.971	0.897	0.972	0.889	983
8	0.967	0.874	0.968	0.863	663
9	0.962	0.886	0.968	0.870	376
10	0.968	0.857	0.971	0.826	131
11	0.970	0.904	0.929	0.899	38
12	0.848	0.654	0.691	0.660	15

Estimands are highly persistent, with the autocorrelations remaining at around .9 even with a ten year lag.

Citywide Effective Regulation

We will now describe the construction of citywide effective regulations, denoted $\bar{\alpha}, \bar{\beta}$ and $\bar{\tau}$.

We begin by first estimating the probability a jurisdiction (county or municipality) is selected into our sample using a probit model. In other words we will estimate

$$\mathbb{P}[Y_j = 1|X_j] = \Phi(X_j'\beta)$$

where $Y_j = 1$ if the jurisdiction is in the sample, and X_j is a vector of covariates for the jurisidiction in 2010.

Given the estimated probability of selection, we calculated the citywide effective regulation, as follows:

$$\bar{x}_c \equiv \frac{\sum_{j=1}^{J_c} x_j \frac{u_j}{\hat{\mathbb{P}}[Y_j=1|X]}}{\sum_{j=1}^{J_c} \frac{u_j}{\hat{\mathbb{P}}[Y_j=1|X]}} \;\forall\; c \in \{1, ..., C\}, \forall\; x \in \{\alpha, \beta, \tau, \text{WRLURI}\}$$

To refresh, $u_j \equiv \sum_{t=1}^{T_j} [(\max_{t' \in T_c} \mathbb{E}_{S_n}[c_{t'}]) - \mathbb{E}_{S_n}[c_t]] * a_t$; $\mathbb{E}_{S_n}[c_t]$ is the sample mean commute time for the tract; and a_t is the area of the tract. Essentially, we are weighting by the inverse probability a jurisdiction will be selected and by the 'inherent' desirability of a location, which in our model is determined by how far away a location is from the city center.

Summary statistics for the citywide effective regulations are presented below.

Table 5.3: Regulatory Indices Summary

	WRLURI	$\bar{\alpha}$	$\bar{\beta}$	$\bar{\tau}$	Frac. Land
Count	629	629	629	629	629
Mean	-0.120	0.878	0.183	1.095	0.833
σ	0.316	0.213	0.054	0.250	0.850
Min	-2.073	0.068	0.061	0.122	0.000
25%	-0.243	0.777	0.156	0.979	0.284
50%	-0.123	0.905	0.181	1.136	0.756
75%	-0.001	1.015	0.202	1.254	1.000
Max	2.538	1.944	0.530	1.721	1.000

Here, 'Fraction of Land' is a percentage which is defined as follows

$$\frac{\sum_{j=1}^{J_c'} u_j}{\sum_{j=1}^{J_c} u_j} \in [0, 1]$$

where J_c' is the number of jurisdictions in city c for which we have regulatory data. Evidently, the distribution of this fraction is skewed to the right, with a majority of cities having most, if not all of their prime land accounted for in the regulatory statistic.

Examining the means of the various statistics, cities are liable to have more robust 'regulatory taxes' and bulk restrictions, exhibiting a diminished propensity to implement robust minimum consumption requirements. Summary statistics on the imputed WRLURI are of note. The mean is slightly below zero. As this value was normalized to one in Gyourko et al. [2021], it would suggest that our sample encompasses cities with less robust land use regimes (a given considerable attention in the paper, given the potential for non-response bias). Further, the standard deviation is less than one (where it was normalized to one in the original paper), which would suggest that there is less variation in the imputed measure than in the original one. Further, the sample is skewed heavily to the left, with over 75% of cities implementing a regulation less than the average of the original paper.

Surrogate Indices

We will now define and describe the construction of the surrogate index for adult income. This work is a refactoring of results from Athey et al. [2016].

Suppose we have two samples at hand, an experimental sample denoted E and an observational sample denoted O. For units in the experimental sample we observe (X_i, Z_i, W_i, S_i), that is we observe covariates, instruments, treatments, and intermediate outcomes. For units in the observational sample we observe (X_i, S_i, Y_i), that is we observe covariates, intermediate outcomes, and final outcomes. Further, suppose that for all units we observe $P_i \in \{\text{O,E}\}$, a binary indicator for which group the unit belongs to.

We will make three assumptions that will allow us to estimate the causal effect of the treatment on final outcomes using several intermediate outcomes.

1. **Exogeneity:** $W_i \mid Z_i \perp\!\!\!\perp Y_i, S_i \mid X_i, P_i = E$

2. **Surrogacy:** $W_i \mid Z_i \perp\!\!\!\perp Y_i \mid S_i, X_i, P_i = E$

3. **Comparability:** $Y_i \mid S_i, X_i, P_i = \text{O} \sim Y_i \mid S_i, X_i, P_i = \text{E}$

Given that we observe (Y_i, S_i, X_i) in the observational sample, we can estimate a model for the final outcomes given covariates and intermediate outcomes, i.e. a surrogate index, defined as follows:

Definition (Surrogate Index): $h_{\text{O}}(s, x) = \mathbb{E}[Y_i \mid S_i = s, X_i = x, P_i = \text{O}]$

Proposition: Given Assumptions 1-3 (exogeneity, surrogacy, and comparability)

$$\mathbb{E}[Y_i \mid \mathbb{E}[W_i|Z_i], X_i, P_i = E] = \mathbb{E}[\ h_{\text{O}}(S_i, X_i) \mid \mathbb{E}[W_i|Z_i], X_i, P_i = E]$$

For a brief proof, please refer to the appendix (B).

This result is directly applicable to the task at hand. We cannot observe the incomes at 35 years of children born in 2000, but we do observe the regulations that were in place in 2010 as well as several intermediate outcomes. Likewise, we cannot observe the regulations in place in 1990, but we can observe intermediate outcomes, as well as the final outcome: income at age 35. It follows that if we can estimate a model of how intermediate outcomes affect income 25 years later, we can identify the effect of land-use regulations on the adult incomes of children born in 2000.

We first tried to estimate $\hat{h}_O(s, x)$ with a linear model. The results of this can be found in D.1. Of particular note are the coefficients on the percent of families that had married heads of household, with a 1% increase in this percentage at the tract-level corresponding to an average decline of $76 for children born to parents in the 25th percentile and an average increase of $60 for children born to parents in the 75th percentile. While these estimates are not causal, the association is at the very least thought provoking.

While the linear model performed well, achieving an adjusted R^2 of .81,.46, .66, and .59 for the average adult income unconditional on parental income, conditional on growing up to parents in the 25th percentile, 50th percentile, and 75th percentile respectively, other models were estimated in order to minimize reconstruction error. These included, but were not limited to elastic net regressions, neural networks, and k-nearest neighbors. Ultimately, 20-nearest neighbors with inverse L^2 weighting trained on a standard normalized covariate set with all interactions performed best, achieving an adjusted R^2 greater than .8 for all outcomes.[4]

With fitted models we were then able to construct the surrogate indices for all outcomes. Descriptive statistics are presented below. It should be noted that all covariates are denominated in 1990 dollars, while outcomes are measured in 2015 dollars.

Table 5.4: Surrogate Indices for Tracts in Urbanized Areas (2010)

	Pooled	25th%	50th%	75th%
Count	1017	1017	1017	1017
Mean	39,188.87	30,676.48	39,962.03	50,270.69
σ	8,266.07	4,809.33	5,344.59	6,490.19
Min	18,634.40	18,542.67	21,994.86	25,298.58
25%	34,292.92	27,936.47	37,264.11	47,765.94
50%	40,407.60	31,381.78	41,152.88	52,233.46
75%	44,720.20	33,887.77	43,605.95	54,409.15
Max	57,605.33	43,261.75	49,877.62	62,571.84

[4] For more on k-nearest neighbors and please refer to the Sci-Kit Learn Documentation, which provides a helpful explainer on the estimation procedure.

Modeling

We now turn to the identification of a causal effect of land-use regulations on adult incomes, the object of the paper. Two models were used to identify this effect, a canonical two-stage least squares model and a generalized structural equation model. Both models require the use of an instrument, in our case, the jurisidictional fragmentation or Gini index.

We estimated two-stage least squares model with the following specifications:

$$\hat{h}_{\mathrm{E}} = \hat{\Pi}_1(\hat{\gamma}g + \hat{\beta}X) + \hat{\Pi}_2 X + \hat{\epsilon} \tag{1}$$

where $\hat{h}_E$ are our surrogate indices, and $\hat{\gamma}$, $\hat{\Pi}_1$ are obtained from regressing the instrument g and tract-level covariates X, on the citywide regulatory indices, $\bar{\alpha}, \bar{\beta}, \bar{\tau}$. In overidentified specifications (that is to say in specifications where there are more instruments than covariates), we will include g^2 in our instrument set.

Generalized Structural Equation Models are a class of models where equations are defined by the researcher that might have any kind of relationship, and the model is estimated by maximum likelihood estimation. In our case, we will estimate the following model:

$$V = \hat{\Pi}_1(\hat{\gamma}g + \hat{\beta}X) + \hat{\Pi}_2 X + \hat{\xi} \tag{2}$$

$$\hat{h}_{\mathrm{E}} = \hat{\Pi}_3[\hat{\Pi}_1(\hat{\gamma}g + \hat{\beta}X) + \hat{\Pi}_2 X] + \hat{\Pi}_4 X + \hat{\epsilon} \tag{3}$$

Where V is vector of tract-level mediating outcomes (i.e. outcomes through which land-use regulations may plausibly affect adult incomes).

Lastly, a Heckman Selection model was used to identify the determinants of land use regulation, or the features of a jurisdiction associated with specific preferences for regulation. The Heckman model is estimated in two stages. In the first stage, the researcher estimates the following statistical object

$$D = \Phi(\hat{\gamma} Z + \hat{\xi}) \tag{4}$$

where Φ is the cumulative distribution function of a normal random variable, D is an indicator of whether the observation is in the sample, and Z are explanatory variables. This is readily accomplished through a canonical probit regression. In the second stage, the researcher estimates:

$$\mathbb{E}[Y|X, D = 1] = \beta X + \mathbb{E}[\epsilon|X, D = 1]$$

Under the assumption that errors are jointly normal, we have

$$\mathbb{E}[Y|X, D = 1] = \beta X + \rho\sigma_\epsilon\lambda(\hat{\gamma} Z)$$

where ρ is the correlation between ξ and ϵ, σ_ϵ is the standard deviation of ϵ, and $\lambda(\hat{\gamma} Z)$ is the inverse Mills Ratio evaluated at $\hat{\gamma} Z$.

6 Results

This section reviews the main findings of this study. We open with a discussion of the *determinants of land-use regulation*, proceed with a discussion of the *causal effect of land use regulation on adult incomes*, and conclude with a consideration of the *causal effect of land use regulation on adult incomes through their effect on mediating impacts*.

Determinants of Land Use Regulation

Before we describe the headline results of the study (namely, the causal effect of land-use regulations on adult incomes), we will first review the results of an investigation into the determinants of land-use regulations, that is to say, the demographic or economic characteristics of a jurisdiction (either a county of municipal government in an urbanized area) that exhibit some relationship with the intensity of land-use regulations. Models were estimated separately for each regulatory index using Heckman Regressions (described in 5) in order to correct for sampling bias over jurisdictions in the construction of the dataset. Full results are reported in Table D.2.

land-use regulations are broadly increasing in the total population of the jurisdiction, though there is heterogeneity in this tendency between indices. The coefficients for the WRLURI and β (the minimum consumption requirement) are positive and significant at the 1%, while the coefficient on τ ('regulatory taxes') are negative and significant at the 1% level.

The structure of local government proves to be a robust predictor of regulatory tendencies. We estimate the coefficients on a county flag (i.e., an indicator of whether the jurisdiction is a county) as negative and significant at the 1% level for all three 'conceptual' measures of intensity. This result is in some ways anticipated by the work of Ortalo-Magné and Prat [2014], which concludes that governments with a mix of urban and rural constituents will choose lower levels of regulation, as rural constituents can only benefit from further urbanization, and hence fewer regulations. As long as counties have reliably more rural constituents than municipalities, this result follows. Further, municipalities may have fewer legal limitations to surmount in order to implement robust land-use regulations. In 'Home Rule' states, municipalities are afforded legal powers not expressly delegated to them by their respective state governments, affording them broad latitude to legislate on behalf of their immediate interests. While further work is required in order to determine the effect

'Home Rule' status on the policy choices made by local governments, it is plausible that such a legal arrangement might lower the cost of implementing burdensome regulations by shielding municipalities from state oversight.

While racial compositions were not on the whole determinative of regulatory tendencies (with the notable exception of the percentage of the population that identified as Asian), the coefficient on an indicator of whether the municipality was whiter than its urbanized area was positive and significant for α and β (at the 5% and 1% level, accordingly). Replicating a finding from Rolleston [1987], this would suggest that, *prima facie*, land-use regulations are at least in part motivated by a racially exclusionary intent.

More surprising than these results perhaps is the absence of any discernible association between homeownership and education with regulatory tendencies. Gyourko et al. [2008] describes a strong positive association between the percentage of the population that possess a tertiary degree, the percentage of households that are homeowners, and the WRLURI. There is a pronounced absence of this tendency in these data, with the only result of any statistical significance being that more educated localities (measured as the percentage of the population that has a bachelor's or graduate degree) and localities with more homeowners exhibit a significant and negative relationship with τ (at the 1% and 5% level, accordingly). This result is orthogonal to the widely touted 'Homevoter Hypothesis' expounded by William Fischel, *inter alia*, which sustains that land-use regulations are the principal way in which homeowners — unable to insure themselves against home equity drops — protect themselves against noxious forms of development (see Fischel [2005]]).

Causal Effect of land-use regulations on Adult Income

Now, on to the main results of the paper, a discussion of the causal effects of land use regulation on adult incomes. Models were estimated separately for each regulatory index using two-stage least squares. Two specifications were deployed: a just identified specification, where the first stage used the Gini index and local covariates, and an overidentified case, where both the Gini index and the index squared were included in the first stage. Full results are reported in the appendix.

Let's now consider the results of the first stages of our estimated 2SLS models.

Table 6.1: 2SLS: First Stage (Tracts)

	(1) WRLURI	(2) α	(3) β	(4) τ
Just Identified				
Gini	-0.245^{**}	0.308^{***}	0.024^{*}	0.306^{***}
	(0.096)	(0.071)	(0.013)	(0.082)
Overidentified				
Gini	6.976^{***}	0.585	0.524^{***}	1.050
	(1.024)	(0.860)	(0.157)	(1.035)
Gini Sq.	-9.624^{***}	-0.368	-0.667^{***}	-0.991
	(1.418)	(1.099)	(0.204)	(1.327)

Heteroskedasticity Robust Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Our instrument is significant for all regulatory indices, albeit at varying levels and with conflicting signs. The WRLURI is declining in the degree of concentration, while the 'conceptual' indices are increasing in concentration. For the overidentified construction, we see that both terms of the quadratic are significant at the 1% level for the WRLURI and for β, suggesting this specification produces a better fit than the just identified case. The first stage F-Statistics largely reproduce the significance results presented in the above table, with the first stages given WRLURI and α producing statistics greater than ten in the overidentified case, and the first stages given α and τ producing statistics greater than ten in the just identified case (see Stock et al. [2002]). While we will limit ourselves to a consideration of these specifications for the remainder of the subsection, results that suffer from weak instrument distortions are included as a point of comparison.

These robust findings provide *prima facie* evidence that 'market power' in the provision of public goods affects the regulatory decisions made by local governments. When concentration increases (alternatively, when fragmentation declines), communities have greater latitude to pursue their narrow interest, as they are unconstrained by the competitive pressures engendered by intra-jurisidictional competition. This result, though unsurprising, has not been demonstrated as of yet in the literature and provides a fertile starting point for a future study.

Let us now consider the results of the second stages of our estimated 2SLS models.

Table 6.2: 2SLS: Second Stage (Tracts)

	(1) Pooled ($10k)	(2) 25th % ($10k)	(3) 50th % ($10k)	(4) 75th % ($10k)
Just Identified				
WRLURI	1.511^{**}	0.462	-0.096	-0.743^{*}
	(0.685)	(0.311)	(0.242)	(0.407)
α	-1.201^{***}	-0.367^{*}	0.076	0.591^{**}
	(0.377)	(0.210)	(0.194)	(0.286)
β	-15.579^{*}	-4.765	0.991	7.664
	(9.071)	(3.503)	(2.589)	(5.433)
τ	-1.210^{***}	-0.370^{*}	0.077	0.595^{**}

	(0.408)	(0.214)	(0.196)	(0.301)
Overidentified				
WRLURI	0.308^{**}	0.166^{*}	-0.065	-0.351^{***}
	(0.134)	(0.092)	(0.084)	(0.118)
α	-1.164^{***}	-0.341	0.065	0.531^{*}
	(0.375)	(0.209)	(0.191)	(0.278)
β	-1.382	0.509	-0.498	-1.917
	(1.722)	(1.264)	(1.078)	(1.438)
τ	-1.075^{***}	-0.289	0.044	0.419
	(0.388)	(0.206)	(0.186)	(0.270)

Covariates in 1990 $, Outcomes in 2015 $

Heteroskedasticity Robust Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Treatment effects are estimated separately

Starting with α we can observe that, all else equal, tracts located in urbanized areas with greater density regulations evidence lower predicted adult incomes for children whose parents are in the 25th percentile of the income distribution. Taking the estimate obtained from the just identified case (which is significant at the 10% level), we observe that a one standard deviation increase in α corresponds to approximately a $787 decline in average annual earnings. Further, α seems to have an even greater impact on the predicted incomes of children born to parents in the 75th percentile of the income distribution. All else equal, a one standard deviation increase in α corresponds to approximately a $1260 increase in predicted incomes (significant at the 5% level). The sign and magnitude of estimated coefficients are virtually identical in the overidentified case, suggesting these estimates are robust to alternative specifications.

τ evinces much the same effect as α, where increased 'regulatory taxes' lower the expected incomes of children born to parents in the 25th percentile and increase the expected incomes of children born to parents in the 75th percentile, with an ambiguous or positive (albeit, imprecise) effect on the incomes of children born to parents in the 50th percentile of the income distribution. Taking our estimates from the just identified case, we observe that a one standard deviation increase in τ corresponds to a \$925 decrease in expected annual incomes for children born to parents in the 25th percentile (significant at the 10% level) and a \$1487 increase in the expected annual incomes for children born parents in the 75th percentile of the income distribution (significant at the 5% level).

Lastly, the WRLURI inverts the distributional effects of the regulatory 'concepts,' increasing the expected earnings of children born to the 25th percentile and decreasing the expected earnings of children born to the 75th percentile. Taking our estimates from the overidentified case, we observe that a one standard deviation increase in the WRLURI corresponds to a \$524 increase in the annual incomes of children born to the 25th percentile (significant at the 10% level) and a \$1109 decrease in the annual incomes of children born to the 75th percentile. In the next section, we give empirical content to the mechanisms through which this effect operates.

It should be noted that though the estimates given β are possibly compromised by distortions due to the choice of a weak instrumental variables, they largely follow the same pattern as the other 'conceptual' regulatory indices in the just identified case, advantaging children born to the 75th percentile at the expense of children born to the 25th percentile.

Causal Effects with Mediating Impacts

In this section, we derive complementary estimates to the ones presented above, proposing three channels or mechanisms through which land-use regulations affect adult incomes: 1) by raising the cost of residing in a neighborhood with higher expected incomes, 2) by decreasing household receipt of public goods, and 3) by increasing housing misspecification, that is to say, shrinking the choice set over which consumers are able to apply their preferences for housing. These channels are measured, correspondingly, by the average expected pooled income divided by the average two-bedroom rent in an urbanized area (i.e., a measure of how costly future incomes are in present rents for an urbanized area), expenditures per capita at the jurisdictional level, and the percent of residential structures in the urbanized area that are single-family homes. A generalized structural equation model was estimated for each regulation separately, where the first stage regressed the regulation on our instrument and tract-level covariates, the second stage regressed the mediating impacts on the exogenized regulatory index and tract-level covariates, and the last stage regressed outcomes on the exogenized intermediary impacts and tract-level covariates. Full results (with controls) are reported in the appendix.

For the sake of simplifying the exposition of our findings, the third stage results are presented before the results of the second (first stage results are omitted as they are indistinguishable from the estimates presented in 6.1).

Table 6.3: GSEM: 3rd Stage Summary

	(1) Pooled	(2) 25th Pctl ($10k)	(3) 50th Pctl ($10k)	(4) 75th Pctl ($10k)
Given WRLURI				
Ad.Inc./Rent ($, UA)	0.053^{***}	0.006	0.017^{*}	0.025^{**}
	(0.016)	(0.010)	(0.009)	(0.012)
Expenditures per Cap (P)	0.132^{***}	0.017	0.042^{*}	0.063^{**}
	(0.037)	(0.023)	(0.022)	(0.029)
Family H (% UA)	-14.376^{***}	-1.605	-4.250	-6.355

	(5.035)	(3.047)	(2.998)	(3.933)
Given α				
Ad.Inc./Rent ($, UA)	0.053***	0.007	0.017*	0.026**
	(0.016)	(0.009)	(0.009)	(0.012)
Expenditures per Cap (P)	0.133***	0.018	0.043*	0.065**
	(0.037)	(0.022)	(0.022)	(0.029)
Family H (% UA)	−14.435***	−1.655	−4.315	−6.435
	(5.027)	(3.034)	(2.985)	(3.930)
Given β				
Ad.Inc./Rent ($, UA)	0.052***	0.006	0.016*	0.025**
	(0.016)	(0.010)	(0.009)	(0.012)
Expenditures per Cap (P)	0.130***	0.016	0.041*	0.064**
	(0.037)	(0.023)	(0.022)	(0.029)
Family H (% UA)	−14.221***	−1.536	−4.220	−6.364
	(5.062)	(3.048)	(2.995)	(3.934)
Given τ				
Ad.Inc./Rent ($, UA)	0.053***	0.007	0.017*	0.025**
	(0.016)	(0.009)	(0.009)	(0.012)
Expenditures per Cap (P)	0.133***	0.018	0.043*	0.064**
	(0.037)	(0.022)	(0.022)	(0.029)
Family H (% UA)	−14.414***	−1.658	−4.312	−6.425
	(5.034)	(3.032)	(2.986)	(3.931)

Covariates in 1990 $, Rents and Outcomes in 2015 $

Heteroskedasticity Robust Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

While numerically different, the third stage results are practically identical for each of the estimated models, suggesting the estimates are robust to alternative specifications. Broadly, for children born to the 75th percentile, adult incomes are decreasing in the effect of regulation through the 'price of opportunity' (the inverse of the quantity used in the model) (significant at the 5% level), increasing in public expenditures (significant at the 5% level), and decreasing in the percent of single-family homes. For children born to parents in the 25th percentile, the sign of the coefficients is identical but with a decidedly smaller magnitude (though this may be due to imprecision in the estimates). While it is unclear why children born to parents in the 25th percentile are less exposed to the effects of land-use regulations, it may be a result of decreased exposure to distortions engendered by land-use regulations in housing consumption and wealth.

We now consider the results of the second stage, which in practice decomposes the effect of land-use regulations on adult incomes into the three proposed channels.

Table 6.4: GSEM: 2nd Stage Summary

	(1) Ad.Inc./Rent ($ UA)	(2) Expenditures per Cap (P)	(3) Family H (% UA)
WRLURI	-165.214^{***}	55.146^{**}	-0.107
	(60.492)	(22.176)	(0.094)
α	131.362^{***}	-43.847^{***}	0.085
	(32.309)	(10.272)	(0.065)
β	1703.469^{*}	-568.592^{*}	1.108

	(955.651)	(317.040)	(0.987)
τ	132.297***	−44.159***	0.086
	(37.439)	(12.060)	(0.066)

Covariates in 1990 \$, Rents and Outcomes in 2015 \$

Heteroskedasticity Robust Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As the above indicates, increasing the WRLURI decreases adult incomes by increasing the 'price of opportunity' (significant at the 1% level), increases adult incomes by increasing governmental expenditures per capita (significant at the 5% level), and by decreasing the percentage of residential structures that are single-family homes. With this, we estimate that 71% of the point estimate of the positive effect of the WRLURI on the adult incomes of children born to the 25th percentile in the 2SLS specification can be explained by these channels. Unexplained remains the negative effect of the WRLURI on the adult incomes of children born to the parents in the 75th percentile.

α operates differently than the WRLURI, increasing adult incomes by decreasing the 'price of opportunity' (significant at the 1%) level and decreasing adult incomes by decreasing expenditures per capita (significant at the 1% level) and increasing the share of single-family homes. Collectively, these three channels account for approximately 3% of the point estimate of the effect of α on the decrease in expected incomes of children born to parents in the 25th percentile and the increase in expected incomes of children born to parents in the 75th percentile in the just identified case. This would suggest that the channels through which α affects incomes in adulthood are unobserved in this specification.

The effects of τ on the three channels are much the same as α, according on both the sign and magnitude of the coefficients.

Lastly, the estimated effects of β, while less precise, merits consideration. If taken at face value, the three channels explain 12% of the decrease in expected incomes of children born to parents in the 25th percentile (just identified case) and 44% of the decrease in incomes of children born to parents in the 75th percentile of the income distribution (over-identified case).

While this analysis provides an accounting of several mechanisms through which land-use regulations act upon the adult incomes of children, it is by no means exhaustive. One plausible channel through which land-use regulations decrease expected incomes in adulthood is by introducing frictions to the movement of households within a city, inducing a spatial distribution of incomes that is unfavorable to upward mobility. In order to study this effect adequately (what is typically denominated a 'neighborhood exposure effect'), we would need access to individual-level, which requires a long and arduous approval process. A future version of this paper will replicate the following analysis with access to de-identified income and demographic data.

7 Conclusion

This paper uses a novel technique for the processing of text data. Where the researchers possess a vector of outcomes or real-world correlates of a text, we show that you can, in principle, extract latent variables that scale in the degree to which a *concept* is inscribed in that text. We apply this technique to the study of land-use regulations, extracting concepts that relate to implicit or explicit caps on development, requirements that homeowners or renters consume a prescribed minimum quantity of housing, and to policies that forestall development, miring it in costly bureaucratic or political processes.

We estimate these concepts for a large corpus of municipal texts scraped from an online repository. We instrument these estimands with a measure of *jurisdictional fragmentation*: the degree to which an urbanized area is divided among various competing governments. Regressing the exogenized regulatory indices on the estimated incomes in adulthood of children born in 2000 who grow up in urbanized areas, we find that land-use regulations have pronounced distributional consequences, advantaging children born to richer parents at the expense of children born to poorer parents. We attempt to account for this effect by introducing *mediating impacts*, plausible channels through which land-use regulations induce the estimated outcomes. While this paper provides convincing, albeit tentative results, we hope to expand on the work done here in future undertakings. In particular, we hope to access de-identified individual-level data, which will allow us to adequately model the effect zoning invariably has on the spatial distribution of incomes, which in turn would allow us to model how zoning affects the formation of neighborhoods and a concomitant *neighborhood exposure effect* on the adult outcomes of children.

References

Susan Athey, Raj Chetty, Guido Imbens, and Hyunseung Kang. Estimating treatment effects using multiple surrogates: The role of the surrogate score and the surrogate index. *arXiv preprint arXiv:1603.09326*, 2016.

Laurie J Bates and Rexford E Santerre. The determinants of restrictive residential zoning: some empirical findings. *Journal of Regional Science*, 34(2):253–263, 1994.

Jan K Brueckner. Testing for strategic interaction among local governments: The case of growth controls. *Journal of urban economics*, 44(3):438–467, 1998.

Raj Chetty and Nathaniel Hendren. The impacts of neighborhoods on intergenerational mobility i: Childhood exposure effects. *The Quarterly Journal of Economics*, 133(3): 1107–1162, 2018.

Raj Chetty, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. Where is the land of opportunity? the geography of intergenerational mobility in the united states. *The Quarterly Journal of Economics*, 129(4):1553–1623, 2014.

Raj Chetty, John N Friedman, Nathaniel Hendren, Maggie R Jones, and Sonya R Porter. The opportunity atlas: Mapping the childhood roots of social mobility. Technical report, National Bureau of Economic Research, 2018.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

William A Fischel. *The homevoter hypothesis: How home values influence local government taxation, school finance, and land-use policies.* Harvard University Press, 2005.

Peter Ganong and Daniel Shoag. Why has regional income convergence in the us declined? *Journal of Urban Economics*, 102:76–90, 2017.

Edward L Glaeser and Bryce A Ward. The causes and consequences of land use regulation: Evidence from greater boston. *Journal of urban Economics*, 65(3):265–278, 2009.

Edward L Glaeser, Joseph Gyourko, and Raven Saks. Why is manhattan so expensive? regulation and the rise in housing prices. *The Journal of Law and Economics*, 48(2): 331–369, 2005.

Edward L Glaeser, Jenny Schuetz, and Bryce Ward. Regulation and the rise of housing prices in greater boston. *Cambridge: Rappaport Institute for Greater Boston, Harvard University and Boston: Pioneer Institute for Public Policy Research*, 2006.

Joseph Gyourko, Albert Saiz, and Anita Summers. A new measure of the local regulatory environment for housing markets: The wharton residential land use regulatory index. *Urban Studies*, 45(3):693–729, 2008.

Joseph Gyourko, Christopher Mayer, and Todd Sinai. Superstar cities. *American Economic Journal: Economic Policy*, 5(4):167–99, 2013.

Joseph Gyourko, Jonathan S Hartley, and Jacob Krimmel. The local residential land use regulatory environment across us housing markets: Evidence from a new wharton index. *Journal of Urban Economics*, 124:103337, 2021.

Bruce W Hamilton. Zoning and the exercise of monopoly power. *Journal of Urban Economics*, 5(1):116–130, 1978.

Christian AL Hilber and Frédéric Robert-Nicoud. On the origins of land use regulations: Theory and evidence from us metro areas. *Journal of Urban Economics*, 75:29–43, 2013.

Chang-Tai Hsieh and Enrico Moretti. Housing constraints and spatial misallocation. *American Economic Journal: Macroeconomics*, 11(2):1–39, 2019.

Ned Levine. The effects of local growth controls on regional housing production and population redistribution in california. *Urban Studies*, 36(12):2047–2068, 1999.

John R Logan, Richard D Alba, Michael Dill, and Min Zhou. Ethnic segmentation in the american metropolis: Increasing divergence in economic incorporation, 1980–1990. *International migration review*, 34(1):98–132, 2000.

Steven Manson, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Ruggles. National historical geographic information system: Version 16.0, 2021.

Andrew D McRae and Mark A Davenport. Low-rank matrix completion and denoising under poisson noise. *Information and Inference: A Journal of the IMA*, 10(2):697–720, 2021.

François Ortalo-Magné and Andrea Prat. On the political economy of urban growth: Homeownership versus affordability. *American Economic Journal: Microeconomics*, 6(1):154–81, 2014.

Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics, 11 2019. URL http://arxiv.org/abs/1908.10084.

Barbara Sherman Rolleston. Determinants of restrictive suburban zoning: An empirical analysis. *Journal of Urban Economics*, 21(1):1–21, 1987. ISSN 0094-1190. doi: https://doi.org/10.1016/0094-1190(87)90019-2. URL https://www.sciencedirect.com/science/article/pii/0094119087900192.

Albert Saiz. The geographic determinants of housing supply. *The Quarterly Journal of Economics*, 125(3):1253–1296, 2010.

James H Stock, Jonathan H Wright, and Motohiro Yogo. A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20(4):518–529, 2002.

Matthew A Turner, Andrew Haughwout, and Wilbert Van Der Klaauw. Land use regulation and welfare. *Econometrica*, 82(4):1341–1403, 2014.

A Methods

Concept Recovery: Outcomes

Table A.1: Outcomes corresponding to α

Question	Values
Is there a hard cap on building permits for single family homes?	Yes (1), No (2)
Is there a hard cap on building permits for multi-family homes?	Yes (1), No (2)
Is there a hard cap on building permits for the number of single family home units authorized for construction?	Yes (1), No (2)
Is there a hard cap on building permits for the number of multi-family home units authorized for construction?	Yes (1), No (2)
Is there a hard cap on building permits for the number of multi-family dwellings authorized?	Yes (1), No (2)
Is there a hard cap on building permits for the number of units in multi-family dwellings?	Yes (1), No (2)
Does your community allow rezoning?	Yes (1), No (2)

Table A.2: Outcomes corresponding to β

Question	Values
Do you have multi-family housing?	Yes (1), No (2)
What is the largest minimum lot size requirement in acres?	<0.5 (1), 0.5-1 (2), 1-2 (3), 2+ (4)

Table A.3: Outcomes corresponding to τ

Question	Values
Does a by-right project require local planning commission approval?	Yes (1), No (2)
Does a by-right project require local zoning board approval?	Yes (1), No (2)
Does a by-right project require local council approval?	Yes (1), No (2)
Does a by-right project require county board commissioners approval?	Yes (1), No (2)
Does a by-right project require county zoning board approval?	Yes (1), No (2)
Does a by-right project require environmental review board approval?	Yes (1), No (2)
Does a by-right project require town meeting approval?	Yes (1), No (2)
Does a by-right project require public health office approval?	Yes (1), No (2)
Does a by-right project require design review board approval?	Yes (1), No (2)
Does a rezoning approval require local zoning board approval?	Y(1), Super-maj.(2), N(3)
Does a rezoning approval require county board commissioners approval?	Y(1), Super-maj.(2), N(3)
Does a rezoning approval require county zoning board approval?	Y(1), Super-maj.(2), N(3)
Does a rezoning approval require environmental review board approval?	Y(1), Super-maj.(2), N(3)
Does a rezoning approval require town meeting approval?	Y(1), Super-maj.(2), N(3)
Does a rezoning approval require public health office approval?	Y(1), Super-maj.(2), N(3)
Is there an affordable housing requirement?	Yes (1), No (2)

B Proofs

Concept Recovery

Proposition: $\nexists\ \nu \neq \nu' \mid \mathcal{W}(v) = \mathcal{W}(v')$

Proof: Proof is by contradiction. Suppose $\exists\ \nu \neq \nu' \mid \mathcal{W}(v) = \mathcal{W}(v')$

$\implies \mathbb{E}_{\mathcal{W}(v)}[\omega] = \mathbb{E}_{\mathcal{W}(v')}[\omega] \implies \nu_d\kappa_k + \mathbb{E}_{\mathcal{D}}[\epsilon_{d,k}] = \nu'_d\kappa_k + \mathbb{E}_{\mathcal{D}}[\epsilon_{d,k}]\ \forall\ d,k \implies \nu_d\kappa_k =$

$\nu'_d\kappa_k \; \forall \; d,k \implies \nu = \nu' \Rightarrow\Leftarrow \nu \neq \nu'$. Q.E.D.

Surrogate Indices

Proposition: Given Assumptions 1-3 (exogeneity, surrogacy, and comparability)

$$\mathbb{E}[Y_i \mid \mathbb{E}[W_i|Z_i], X_i, P_i = E] = \mathbb{E}[\; h_{\mathrm{O}}(S_i, X_i) \mid \mathbb{E}[W_i|Z_i], X_i, P_i = E]$$

Proof: The law of iterated expectations states

$$\begin{aligned}
\mathbb{E}[Y_i \mid \mathbb{E}[W_i|Z_i], X_i, P_i = E] &= \mathbb{E}[\; \mathbb{E}[Y_i \mid \mathbb{E}[W_i|Z_i], S_i, X_i, P_i = E] \mid \mathbb{E}[W_i|Z_i], X_i, P_i = E] \\
\{\text{By A2}\} \; &= \mathbb{E}[\; \mathbb{E}[Y_i \mid S_i, X_i, P_i = E] \mid \mathbb{E}[W_i|Z_i], X_i, P_i = E] \\
\{\text{By Def.}\} \; &= \mathbb{E}[\; h_{\mathrm{E}}(S_i, X_i) \mid \mathbb{E}[W_i|Z_i], X_i, P_i = E] \\
\{\text{By A3}\} \; &= \mathbb{E}[\; h_{\mathrm{O}}(S_i, X_i) \mid \mathbb{E}[W_i|Z_i], X_i, P_i = E]
\end{aligned}$$

Q.E.D.

C Summary Statistics

Table C.1: Tract-Level Covariates

	Mean	SD	Min	Max
Ln Total Pop.	7.394	0.472	1.099	9.602
Female (%)	0.512	0.035	0.002	1.000
White (%)	0.584	0.284	0.000	1.000
Black (%)	0.169	0.238	0.000	1.000
Asian (%)	0.027	0.029	0.000	0.301
Hispanic (%)	0.195	0.213	0.000	1.000
<18 y.o. (%)	0.226	0.076	0.000	0.667
Single Parent Families (%)	0.375	0.170	0.000	1.000

Child w/ Parents (%)	0.858	0.100	0.000	1.000
>1hr Commute (%)	0.061	0.051	0.000	1.000
<20m Commute (%)	0.288	0.112	0.000	1.000
Grad. or Bachelors (%)	0.293	0.182	0.000	1.000
HS Drop (%)	0.145	0.116	0.000	0.702
<$15k (%)	0.242	0.153	0.000	1.000
$35-75k (%)	0.292	0.118	0.000	1.000
>$125k (%)	0.045	0.074	0.000	0.736
Poor Families (%)	0.114	0.115	0.000	1.000
Foreign Born (%)	0.151	0.149	0.000	1.000
Observations	7152			

Covariates in 1990 $

D Regressions

D.1 Determinants of Adult Income

Table D.1: OLS: Income at Age 35 (Tracts)

	(1) Pooled ($10k)	(2) 25th % ($10k)	(3) 50th % ($10k)	(4) 75th % ($10k)
Ln Total Pop.	-522.102^{***}	-1311.554^{***}	-1101.920^{***}	-976.063^{***}
	(58.952)	(99.014)	(53.440)	(69.745)
Female (%)	-7203.265^{***}	-6715.436^{***}	-4959.738^{***}	-1256.645
	(1708.690)	(2112.089)	(1438.623)	(1866.735)

White (%)	12895.482***	9269.746***	10092.268***	12265.842***
	(1102.907)	(1634.368)	(1153.747)	(1855.344)
Black (%)	−2683.978	−1645.355	424.998	3297.680
	(2034.379)	(2543.880)	(1860.568)	(2546.353)
Asian (%)	26811.460***	35910.585***	35586.146***	34849.501***
	(3171.213)	(5026.414)	(4008.990)	(5815.259)
Hispanic (%)	8663.451***	9656.831***	10403.886***	12304.064***
	(841.448)	(1150.034)	(898.424)	(1441.395)
>65 y.o. (%)	12049.387***	11428.762***	12669.664***	12466.713***
	(999.996)	(1949.900)	(875.992)	(1115.694)
<18 y.o. (%)	13082.542***	23854.576***	18483.855***	10180.165***
	(1963.674)	(2249.408)	(1690.970)	(2108.193)
Married HH (%)	1765.105	390.592	−1322.076	−2375.079
	(1444.279)	(1845.304)	(1339.438)	(1536.929)
Married Families (%)	2290.213	−7642.951***	−1304.754	6050.488***
	(1413.349)	(1408.961)	(1200.417)	(1486.917)
Single Parent HH (%)	−11510.020***	−17331.008***	−18727.129***	−18328.003***
	(2266.098)	(2775.125)	(1976.855)	(2638.458)
Single Parent Families (%)	−17646.039***	−13893.666***	−14135.440***	−15392.448***
	(1077.104)	(1033.275)	(906.289)	(1175.832)
Single HH (%)	−3006.611**	−8526.242***	−6950.363***	−4328.742***
	(1498.890)	(1792.039)	(1375.822)	(1623.406)
Child w/ Parents (%)	748.965	−644.449	101.489	370.023

	(979.932)	(991.044)	(806.666)	(1143.675)
Child w/ Relatives (%)	-22961.891^{***}	-10459.406^{*}	-14604.014^{***}	-14151.177^{***}
	(1489.384)	(6140.204)	(1299.447)	(1621.168)
Child in Foster (%)	-38372.006^{***}	-32254.645^{***}	-32336.928^{***}	-36061.245^{***}
	(3185.919)	(3935.938)	(2473.376)	(3299.720)
Vacant Houses (%)	-9514.164^{***}	-3076.017^{***}	-4695.734^{***}	-6512.413^{***}
	(524.338)	(512.528)	(460.836)	(601.625)
Owner Occupied H (%)	-2591.691^{*}	970.805	-811.169	-3459.077
	(1373.879)	(1199.298)	(1384.322)	(2140.825)
White H.owner (%)	7927.555^{***}	4042.537^{**}	4886.404^{***}	5833.235^{***}
	(1464.255)	(1583.618)	(1467.859)	(2242.334)
Black H.owner (%)	7199.918^{***}	4041.012	4986.123^{**}	5228.840^{*}
	(2300.310)	(3227.487)	(2073.760)	(2902.512)
Asian H.owner (%)	-12121.217^{***}	-19345.776^{***}	-18738.999^{***}	-16888.793^{**}
	(3869.120)	(5812.915)	(4715.055)	(6793.121)
White Renter (%)	-4137.139^{***}	1885.807^{**}	616.044	-816.600
	(1115.660)	(957.140)	(1023.178)	(1553.528)
Black Renter (%)	2867.517	5963.906^{**}	3208.154^{*}	-239.640
	(2218.559)	(2426.717)	(1928.902)	(2607.953)
Asian Renter (%)	-19043.593^{***}	-20663.708^{***}	-21531.624^{***}	-20854.845^{***}
	(3489.754)	(5711.142)	(4619.680)	(6757.699)
<$15k H Value (%)	3668.253^{***}	6880.846^{***}	6466.801^{***}	6118.055^{***}
	(466.703)	(557.757)	(502.925)	(717.978)

>$500k H Value (%)	3844.018***	2422.697***	1660.645**	504.526
	(807.597)	(935.075)	(772.434)	(946.420)
$15k-$45k H Value (%)	−6645.558***	−2729.027***	−2973.504***	−3209.399***
	(224.025)	(260.493)	(199.285)	(278.943)
$150k-$500k H Value (%)	6932.031***	5006.828***	4709.664***	4084.923***
	(288.423)	(435.658)	(261.483)	(323.229)
H Median Value ($)	0.010***	0.001	0.002	0.004**
	(0.002)	(0.002)	(0.001)	(0.002)
H Agg. Value ($)	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
H.owners White (%)	−5201.101***	−2846.493***	−1400.287**	431.858
	(687.118)	(734.800)	(627.802)	(798.477)
H.owners Black (%)	2010.586***	1219.443*	1031.096*	824.446
	(694.567)	(671.132)	(625.739)	(886.423)
H.owners Asian (%)	−2112.922*	−806.316	−482.871	−210.744
	(1114.696)	(1177.104)	(1139.622)	(1560.984)
<$100 Rent (%)	−3384.124***	−1475.164	4799.283***	11810.968***
	(574.260)	(928.391)	(602.504)	(909.190)
>$1000 Rent (%)	18068.449***	12758.535***	13613.225***	14889.462***
	(821.350)	(973.121)	(794.925)	(812.617)
$100-$400 Rent (%)	3811.671***	288.143	2358.182***	3173.426***
	(340.437)	(1551.267)	(310.701)	(380.493)
$500-$1000 Rent(%)	7746.729***	5119.427***	5799.904***	5680.993***

	(437.729)	(1012.325)	(397.938)	(449.921)
Rent Median (\$)	−19.393***	−12.551***	−13.278***	−16.130***
	(0.677)	(1.693)	(0.648)	(0.699)
Rent Agg. (%)	−0.003***	0.002**	0.001	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Single Family H (%)	−14381.280***	−9631.196***	−9565.606***	−8288.721***
	(2653.341)	(3384.844)	(2539.803)	(2861.259)
Single Fam (Attach) (%)	−9290.534***	−4758.000	−4167.590	−2216.335
	(2661.260)	(3344.017)	(2543.813)	(2878.474)
2-9 Units (%)	−9259.528***	−4688.075	−4468.539*	−2890.383
	(2646.457)	(3376.560)	(2547.215)	(2876.038)
10-50 Units (%)	−6294.031**	−2141.299	−2481.191	−1611.613
	(2650.199)	(3355.439)	(2543.269)	(2860.501)
Mobile Homes (%)	−24329.422***	−14715.299***	−14284.933***	−12448.616***
	(2661.736)	(3466.043)	(2539.900)	(2872.922)
>1hr Commute (%)	2028.042***	7061.585***	5741.391***	5957.404***
	(531.591)	(1376.252)	(517.983)	(661.054)
<20m Commute (%)	2205.664***	328.952	2731.936***	5981.279***
	(200.196)	(236.968)	(178.069)	(233.186)
Private Prim./Sec. (%)	18.995	−721.480**	−342.681	94.914
	(325.985)	(315.052)	(285.317)	(332.236)
Grad. Deg. (%)	366.979	−7781.504***	−8078.276***	−8971.012***
	(922.122)	(1038.708)	(879.039)	(989.929)

Bachelors Deg. (%)	15113.232***	9923.366***	10093.843***	10378.114***
	(816.451)	(859.312)	(743.164)	(874.579)
Some College (%)	−8827.561***	−1363.580**	−5640.436***	−11436.895***
	(577.040)	(562.594)	(486.342)	(628.565)
HS Drop (%)	−15465.509***	−12618.441***	−11461.259***	−11846.858***
	(511.819)	(1126.182)	(452.814)	(592.837)
<$15k (%)	2906.365***	5039.786***	4921.591***	5216.252***
	(671.311)	(693.693)	(600.380)	(800.752)
$35-75k (%)	5386.353***	967.398	901.324**	1377.992***
	(504.594)	(619.076)	(422.376)	(521.469)
>$125k (%)	16288.947***	−4056.742**	−1613.087	−12.422
	(1377.385)	(1870.554)	(1310.708)	(1332.246)
On Public Asst. (%)	3343.239***	190.901	−2287.260***	−4320.877***
	(722.842)	(830.625)	(691.495)	(1011.993)
Poor Families (%)	−2205.997***	−901.558**	−666.160*	−228.265
	(476.670)	(420.301)	(401.327)	(570.821)
Foreign Born (%)	−2507.686***	7606.732***	5340.355***	3321.926***
	(502.784)	(581.270)	(468.348)	(674.169)
Constant	58675.755***	48150.868***	52113.649***	55910.797***
	(3218.297)	(4061.387)	(3206.487)	(3692.045)
Observations	49529	49529	49529	49529
Adj. R^2	0.811	0.466	0.665	0.590

Covariates in 1990 $, Outcomes in 2015 $

Heteroskedasticity Robust Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D.2 Determinants of Land Use Regulations

Table D.2: Heckman: Regulatory Indices (Places)

	(1) WRLURI	(2) α	(3) β	(4) τ
Ln Total Pop.	0.067***	0.006	0.013***	−0.064***
	(0.018)	(0.006)	(0.005)	(0.012)
County Flag	0.048*	−0.125***	−0.016***	−0.174***
	(0.028)	(0.019)	(0.006)	(0.030)
>65 y.o. (%)	0.724**	−0.116	−0.045	0.125
	(0.287)	(0.216)	(0.050)	(0.234)
<18 y.o. (%)	−0.041	0.323	−0.017	−0.518
	(0.477)	(0.277)	(0.078)	(0.368)
White (%)	−0.181	0.183	−0.060*	0.440**
	(0.202)	(0.131)	(0.036)	(0.177)
Black (%)	0.103	0.201	0.040	0.157
	(0.202)	(0.129)	(0.038)	(0.170)
Asian (%)	−2.020***	−0.096	−0.520***	2.639***
	(0.533)	(0.330)	(0.108)	(0.611)
Hispanic (%)	0.114	0.282**	0.037	0.248

	(0.185)	(0.121)	(0.034)	(0.170)
Whiter than UA (P)	0.003	0.026^{**}	0.011^{***}	−0.005
	(0.024)	(0.013)	(0.004)	(0.020)
Married Families (%)	−0.279	−0.167	−0.038	0.619^{*}
	(0.403)	(0.252)	(0.072)	(0.357)
Single HH (%)	−0.345	0.067	0.146^{**}	-0.737^{**}
	(0.356)	(0.204)	(0.057)	(0.288)
H.owners (%)	−0.066	−0.124	0.050^{*}	-0.282^{**}
	(0.169)	(0.107)	(0.029)	(0.136)
>1hr Commute (%)	−0.130	−0.157	-0.166^{***}	0.298
	(0.235)	(0.155)	(0.046)	(0.201)
<20m Commute (%)	0.062	−0.020	-0.053^{**}	0.166
	(0.126)	(0.075)	(0.022)	(0.108)
Bachelors or Grad (%)	0.083	−0.059	0.004	-0.411^{***}
	(0.162)	(0.100)	(0.031)	(0.132)
<$15k (%)	−0.035	-0.255^{**}	0.050	−0.249
	(0.214)	(0.129)	(0.035)	(0.167)
$35-75k (%)	0.153	−0.107	−0.013	0.135
	(0.234)	(0.155)	(0.038)	(0.200)
>$125k (%)	0.230	0.066	0.136	0.073
	(0.389)	(0.288)	(0.090)	(0.304)
Foreign Born (%)	0.591^{***}	-0.265^{***}	−0.027	−0.087
	(0.178)	(0.093)	(0.031)	(0.173)

Constant	−1.375***	0.757***	−0.101***	2.530***
	(0.162)	(0.056)	(0.029)	(0.097)
Sample Flag				
Ln Total Pop.	0.155***	0.154***	0.150***	0.151***
	(0.034)	(0.034)	(0.039)	(0.035)
County Flag	0.051	0.063	0.054	0.065
	(0.047)	(0.048)	(0.047)	(0.047)
>65 y.o. (%)	−0.053	−0.052	−0.016	0.022
	(0.324)	(0.329)	(0.322)	(0.327)
<18 y.o. (%)	1.257**	1.280**	1.143**	1.216**
	(0.539)	(0.543)	(0.532)	(0.537)
White (%)	−0.773***	−0.744***	−0.740***	−0.752***
	(0.246)	(0.247)	(0.251)	(0.248)
Black (%)	0.156	0.148	0.153	0.146
	(0.250)	(0.252)	(0.259)	(0.254)
Asian (%)	−6.010***	−6.000***	−5.875***	−6.024***
	(0.926)	(0.943)	(0.955)	(0.941)
Hispanic (%)	−0.226	−0.200	−0.189	−0.268
	(0.245)	(0.246)	(0.251)	(0.247)
Whiter than UA (P)	0.080**	0.074**	0.081**	0.075**
	(0.034)	(0.034)	(0.034)	(0.034)
Married Families (%)	−0.691	−0.714	−0.505	−0.608
	(0.523)	(0.527)	(0.510)	(0.516)

Single HH (%)	2.109***	2.068***	2.042***	2.076***
	(0.432)	(0.433)	(0.423)	(0.426)
H.owners (%)	0.267	0.246	0.207	0.225
	(0.189)	(0.189)	(0.189)	(0.186)
>1hr Commute (%)	−1.468***	−1.440***	−1.494***	−1.462***
	(0.316)	(0.319)	(0.322)	(0.314)
<20m Commute (%)	−0.538***	−0.525***	−0.492***	−0.532***
	(0.157)	(0.158)	(0.157)	(0.156)
Bachelors or Grad (%)	0.647***	0.632***	0.568**	0.625***
	(0.220)	(0.222)	(0.229)	(0.221)
<$15k (%)	0.158	0.202	0.168	0.208
	(0.254)	(0.256)	(0.249)	(0.253)
$35-75k (%)	−0.525*	−0.498*	−0.503*	−0.501*
	(0.287)	(0.291)	(0.286)	(0.287)
>$125k (%)	−0.289	−0.224	0.114	−0.193
	(0.556)	(0.556)	(0.636)	(0.560)
Foreign Born (%)	0.233	0.143	0.191	0.335
	(0.260)	(0.256)	(0.255)	(0.254)
Constant	−2.648***	−2.650***	−2.620***	−2.621***
	(0.209)	(0.211)	(0.234)	(0.214)
arctanhρ	1.274***	0.148*	1.977***	−1.999***
	(0.110)	(0.076)	(0.077)	(0.078)
$\ln \sigma$	−0.649***	−1.538***	−2.242***	−0.688***

	(0.072)	(0.027)	(0.059)	(0.035)
Observations	16501	16501	16501	16501

Covariates in 1990 $

Heteroskedasticity Robust Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D.3 Causal Effect of Regulation on Adult Income

First Stage

Table D.3: 2SLS (Just Identified): First Stage

	(1)	(2)	(3)	(4)
	WRLURI	α	β	τ
Gini	-0.245^{**}	0.308^{***}	0.024^{*}	0.306^{***}
	(0.096)	(0.071)	(0.013)	(0.082)
Ln Total Pop.	0.009	0.030^{***}	0.007^{***}	0.044^{***}
	(0.009)	(0.005)	(0.001)	(0.007)
Female (%)	-0.219^{*}	-0.070	-0.008	-0.132
	(0.131)	(0.082)	(0.020)	(0.106)
White (%)	-0.315^{***}	0.282^{***}	-0.024^{**}	0.307^{***}
	(0.075)	(0.076)	(0.010)	(0.096)
Black (%)	-0.338^{***}	0.348^{***}	0.012	0.435^{***}
	(0.070)	(0.073)	(0.009)	(0.093)
Asian (%)	-1.072^{***}	-0.531^{***}	-0.230^{***}	-0.804^{***}

	(0.139)	(0.123)	(0.021)	(0.152)
Hispanic (%)	−0.192**	0.270***	−0.020*	0.293***
	(0.077)	(0.077)	(0.011)	(0.099)
<18 y.o. (%)	−0.369***	−0.069	−0.030***	−0.108*
	(0.076)	(0.047)	(0.011)	(0.057)
Single Parent Families (%)	0.196***	−0.179***	−0.029***	−0.221***
	(0.036)	(0.024)	(0.005)	(0.028)
Child w/ Parents (%)	−0.211***	0.007	−0.014**	0.011
	(0.044)	(0.029)	(0.006)	(0.035)
>1hr Commute (%)	0.220***	−0.079**	0.010	−0.125***
	(0.063)	(0.039)	(0.008)	(0.047)
<20m Commute (%)	−0.195***	0.047**	−0.002	0.030
	(0.034)	(0.022)	(0.005)	(0.026)
Grad. or Bachelors (%)	−0.188***	0.045	−0.008	0.025
	(0.037)	(0.027)	(0.006)	(0.032)
HS Drop (%)	−0.927***	−0.283***	−0.092***	−0.428***
	(0.056)	(0.036)	(0.008)	(0.043)
<$15k (%)	−0.092*	0.154***	0.038***	0.205***
	(0.055)	(0.035)	(0.008)	(0.042)
$35-75k (%)	0.166***	−0.152***	−0.018**	−0.189***
	(0.047)	(0.032)	(0.007)	(0.039)
>$125k (%)	0.495***	−0.297***	0.001	−0.306***
	(0.075)	(0.047)	(0.011)	(0.057)

Poor Families (%)	0.165***	0.004	−0.015*	−0.033
	(0.055)	(0.037)	(0.007)	(0.044)
Foreign Born (%)	1.306***	0.040	0.090***	0.186***
	(0.041)	(0.028)	(0.005)	(0.034)
Constant	0.648***	0.417***	0.185***	0.577***
	(0.109)	(0.095)	(0.016)	(0.118)
Observations	7152	7152	7152	7152

Covariates in 1990 $

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.4: 2SLS (Overdentified): First Stage

	(1)	(2)	(3)	(4)
	WRLURI	α	β	τ
Gini	6.976***	0.585	0.524***	1.050
	(1.024)	(0.860)	(0.157)	(1.035)
Gini Sq.	−9.624***	−0.368	−0.667***	−0.991
	(1.418)	(1.099)	(0.204)	(1.327)
Ln Total Pop.	0.012	0.031***	0.007***	0.044***
	(0.009)	(0.005)	(0.001)	(0.007)
Female (%)	−0.198	−0.069	−0.006	−0.130
	(0.133)	(0.082)	(0.020)	(0.106)
White (%)	−0.273***	0.284***	−0.021**	0.312***

	(0.075)	(0.075)	(0.010)	(0.096)
Black (%)	-0.276^{***}	0.351^{***}	0.017^{*}	0.441^{***}
	(0.070)	(0.072)	(0.009)	(0.093)
Asian (%)	-1.057^{***}	-0.531^{***}	-0.229^{***}	-0.803^{***}
	(0.138)	(0.123)	(0.021)	(0.152)
Hispanic (%)	-0.145^{*}	0.272^{***}	-0.017	0.298^{***}
	(0.077)	(0.077)	(0.011)	(0.098)
<18 y.o. (%)	-0.436^{***}	-0.072	-0.034^{***}	-0.115^{**}
	(0.077)	(0.048)	(0.011)	(0.058)
Single Parent Families (%)	0.192^{***}	-0.179^{***}	-0.029^{***}	-0.221^{***}
	(0.036)	(0.024)	(0.005)	(0.028)
Child w/ Parents (%)	-0.195^{***}	0.007	-0.013^{**}	0.013
	(0.044)	(0.029)	(0.006)	(0.035)
>1hr Commute (%)	0.234^{***}	-0.078^{**}	0.012	-0.124^{***}
	(0.062)	(0.040)	(0.008)	(0.047)
<20m Commute (%)	-0.166^{***}	0.048^{**}	0.000	0.033
	(0.034)	(0.022)	(0.005)	(0.026)
Grad. or Bachelors (%)	-0.163^{***}	0.046^{*}	-0.006	0.028
	(0.037)	(0.027)	(0.006)	(0.032)
HS Drop (%)	-0.911^{***}	-0.282^{***}	-0.091^{***}	-0.426^{***}
	(0.055)	(0.036)	(0.008)	(0.042)
<$15k (%)	-0.076	0.154^{***}	0.039^{***}	0.206^{***}
	(0.056)	(0.035)	(0.008)	(0.042)

\$35-75k (%)	0.162***	−0.152***	−0.018**	−0.189***
	(0.047)	(0.032)	(0.007)	(0.039)
>\$125k (%)	0.475***	−0.298***	−0.000	−0.308***
	(0.075)	(0.047)	(0.011)	(0.057)
Poor Families (%)	0.171***	0.004	−0.014*	−0.032
	(0.055)	(0.037)	(0.007)	(0.043)
Foreign Born (%)	1.293***	0.040	0.089***	0.185***
	(0.040)	(0.028)	(0.005)	(0.033)
Constant	−0.783***	0.363*	0.086**	0.430*
	(0.217)	(0.187)	(0.034)	(0.229)
Observations	7152	7152	7152	7152

Covariates in 1990 \$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

WRLURI

Table D.5: 2SLS (Just Identified): WRLURI (Tracts)

	(1)	(2)	(3)	(4)
	Pooled	25th Pctl (\$10k)	50th Pctl (\$10k)	75th Pctl (\$10k)
WRLURI	1.511**	0.462	−0.096	−0.743*
	(0.685)	(0.311)	(0.242)	(0.407)
Ln Total Pop.	−0.016	−0.031***	−0.011	0.011

	(0.017)	(0.009)	(0.007)	(0.011)
Female (%)	−0.274	−0.175	−0.491***	−0.846***
	(0.296)	(0.130)	(0.120)	(0.186)
White (%)	2.159***	1.160***	1.076***	1.007***
	(0.314)	(0.146)	(0.157)	(0.237)
Black (%)	0.304	−0.115	−0.535***	−1.056***
	(0.318)	(0.147)	(0.157)	(0.238)
Asian (%)	3.087***	1.381***	0.883***	0.316
	(0.811)	(0.369)	(0.318)	(0.517)
Hispanic (%)	1.242***	0.839***	0.729***	0.609***
	(0.259)	(0.122)	(0.145)	(0.215)
<18 y.o. (%)	1.949***	0.700***	0.484***	0.230
	(0.309)	(0.142)	(0.111)	(0.183)
Single Parent Families (%)	−1.764***	−0.877***	−0.872***	−0.915***
	(0.156)	(0.074)	(0.062)	(0.098)
Child w/ Parents (%)	0.417**	0.118	0.127	0.133
	(0.182)	(0.090)	(0.080)	(0.116)
>1hr Commute (%)	0.217	0.593***	0.500***	0.416***
	(0.197)	(0.088)	(0.074)	(0.120)
<20m Commute (%)	0.147	−0.017	−0.008	0.008
	(0.152)	(0.072)	(0.058)	(0.094)
Grad. or Bachelors (%)	1.529***	0.574***	0.449***	0.313***
	(0.159)	(0.073)	(0.056)	(0.090)

HS Drop (%)	0.826	0.028	-0.395^{*}	-0.893^{**}
	(0.643)	(0.292)	(0.227)	(0.381)
<\$15k (%)	0.050	0.125^{**}	0.095^{*}	0.064
	(0.126)	(0.061)	(0.053)	(0.081)
\$35-75k (%)	0.466^{***}	0.129^{*}	0.136^{**}	0.139
	(0.149)	(0.070)	(0.061)	(0.095)
>\$125k (%)	2.794^{***}	1.383^{***}	1.375^{***}	1.344^{***}
	(0.396)	(0.183)	(0.141)	(0.224)
Poor Families (%)	-0.463^{***}	-0.098	-0.052	0.017
	(0.151)	(0.071)	(0.059)	(0.094)
Foreign Born (%)	-2.364^{***}	-0.680^{*}	-0.026	0.727
	(0.904)	(0.411)	(0.321)	(0.537)
Constant	2.057^{***}	2.448^{***}	3.542^{***}	4.762^{***}
	(0.484)	(0.226)	(0.206)	(0.313)
Observations	7152	7152	7152	7152
Adj. R^2	0.843	0.863	0.912	0.848
Cragg-Donald (F-Stat)	6.549	6.549	6.549	6.549

Covariates in 1990 \$, Outcomes in 2015 \$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.6: 2SLS (Overdentified): WRLURI (Tracts)

	(1)	(2)	(3)	(4)

	Pooled	25th Pctl ($10k)	50th Pctl ($10k)	75th Pctl ($10k)
WRLURI	0.308^{**}	0.166^{*}	-0.065	-0.351^{***}
	(0.134)	(0.092)	(0.084)	(0.118)
Ln Total Pop.	-0.007	-0.028^{***}	-0.011	0.008
	(0.011)	(0.008)	(0.007)	(0.009)
Female (%)	-0.522^{**}	-0.236^{**}	-0.484^{***}	-0.765^{***}
	(0.207)	(0.107)	(0.115)	(0.150)
White (%)	1.776^{***}	1.066^{***}	1.086^{***}	1.132^{***}
	(0.185)	(0.103)	(0.142)	(0.210)
Black (%)	-0.102	-0.215^{**}	-0.524^{***}	-0.924^{***}
	(0.179)	(0.099)	(0.139)	(0.206)
Asian (%)	1.806^{***}	1.065^{***}	0.916^{***}	0.733^{**}
	(0.311)	(0.182)	(0.209)	(0.297)
Hispanic (%)	1.010^{***}	0.782^{***}	0.735^{***}	0.685^{***}
	(0.179)	(0.098)	(0.140)	(0.207)
<18 y.o. (%)	1.475^{***}	0.583^{***}	0.496^{***}	0.384^{***}
	(0.107)	(0.072)	(0.066)	(0.086)
Single Parent Families (%)	-1.517^{***}	-0.816^{***}	-0.878^{***}	-0.995^{***}
	(0.067)	(0.041)	(0.040)	(0.052)
Child w/ Parents (%)	0.166	0.056	0.133^{**}	0.215^{***}
	(0.103)	(0.062)	(0.063)	(0.080)
>1hr Commute (%)	0.487^{***}	0.659^{***}	0.493^{***}	0.328^{***}
	(0.095)	(0.056)	(0.054)	(0.072)

<20m Commute (%)	-0.100^{*}	-0.078^{**}	-0.002	0.089^{**}
	(0.057)	(0.036)	(0.034)	(0.044)
Grad. or Bachelors (%)	1.294^{***}	0.517^{***}	0.455^{***}	0.389^{***}
	(0.056)	(0.037)	(0.034)	(0.043)
HS Drop (%)	-0.291^{**}	-0.247^{***}	-0.366^{***}	-0.529^{***}
	(0.142)	(0.095)	(0.089)	(0.124)
<$15k (%)	-0.068	0.095^{*}	0.098^{**}	0.103^{*}
	(0.083)	(0.050)	(0.048)	(0.062)
$35-75k (%)	0.668^{***}	0.179^{***}	0.131^{***}	0.073
	(0.079)	(0.047)	(0.046)	(0.060)
>$125k (%)	3.420^{***}	1.537^{***}	1.358^{***}	1.140^{***}
	(0.124)	(0.081)	(0.071)	(0.090)
Poor Families (%)	-0.270^{***}	-0.051	-0.057	-0.046
	(0.078)	(0.048)	(0.047)	(0.063)
Foreign Born (%)	-0.779^{***}	-0.290^{**}	-0.067	0.210
	(0.185)	(0.126)	(0.115)	(0.161)
Constant	2.739^{***}	2.616^{***}	3.524^{***}	4.539^{***}
	(0.264)	(0.148)	(0.167)	(0.226)
Observations	7152	7152	7152	7152
Adj. R^2	0.928	0.887	0.913	0.890
Cragg-Donald (F-Stat)	23.215	23.215	23.215	23.215
Hansen (J-Stat)	10.698	1.390	0.020	1.805

Covariates in 1990 $, Outcomes in 2015 $

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Alpha

Table D.7: 2SLS (Just Identified): α (Tracts)

	(1)	(2)	(3)	(4)
	Pooled	25th Pctl (\$10k)	50th Pctl (\$10k)	75th Pctl (\$10k)
α	-1.201^{***}	-0.367^{*}	0.076	0.591^{**}
	(0.377)	(0.210)	(0.194)	(0.286)
Ln Total Pop.	0.033^{*}	-0.016	-0.014	-0.013
	(0.018)	(0.010)	(0.009)	(0.012)
Female (%)	-0.688^{***}	-0.301^{***}	-0.464^{***}	-0.642^{***}
	(0.208)	(0.102)	(0.118)	(0.168)
White (%)	2.023^{***}	1.119^{***}	1.085^{***}	1.074^{***}
	(0.264)	(0.122)	(0.150)	(0.233)
Black (%)	0.212	-0.144	-0.529^{***}	-1.011^{***}
	(0.268)	(0.126)	(0.152)	(0.235)
Asian (%)	0.829^{**}	0.690^{***}	1.026^{***}	1.427^{***}
	(0.396)	(0.204)	(0.215)	(0.318)
Hispanic (%)	1.276^{***}	0.849^{***}	0.727^{***}	0.592^{**}
	(0.262)	(0.120)	(0.148)	(0.231)
<18 y.o. (%)	1.309^{***}	0.504^{***}	0.524^{***}	0.545^{***}

	(0.110)	(0.062)	(0.060)	(0.082)
Single Parent Families (%)	−1.682***	−0.852***	−0.877***	−0.955***
	(0.097)	(0.055)	(0.052)	(0.070)
Child w/ Parents (%)	0.107	0.023	0.147**	0.286***
	(0.106)	(0.059)	(0.061)	(0.075)
>1hr Commute (%)	0.454***	0.665***	0.485***	0.299***
	(0.107)	(0.055)	(0.054)	(0.075)
<20m Commute (%)	−0.092	−0.090***	0.007	0.126***
	(0.061)	(0.034)	(0.031)	(0.040)
Grad. or Bachelors (%)	1.299***	0.504***	0.463***	0.426***
	(0.057)	(0.034)	(0.033)	(0.047)
HS Drop (%)	−0.913***	−0.504***	−0.284***	−0.037
	(0.134)	(0.076)	(0.074)	(0.104)
<$15k (%)	0.096	0.139**	0.092	0.042
	(0.103)	(0.058)	(0.057)	(0.078)
$35-75k (%)	0.535***	0.150***	0.132**	0.105
	(0.101)	(0.056)	(0.054)	(0.073)
>$125k (%)	3.184***	1.503***	1.350***	1.152***
	(0.164)	(0.093)	(0.090)	(0.128)
Poor Families (%)	−0.208**	−0.020	−0.068	−0.109*
	(0.081)	(0.045)	(0.044)	(0.063)
Foreign Born (%)	−0.342***	−0.062*	−0.154***	−0.268***
	(0.059)	(0.034)	(0.031)	(0.044)

Constant	3.537***	2.901***	3.448***	4.033***
	(0.343)	(0.178)	(0.192)	(0.278)
Observations	7152	7152	7152	7152
Adj. R^2	0.906	0.882	0.913	0.884
Cragg-Donald (F-Stat)	18.988	18.988	18.988	18.988

Covariates in 1990 \$, Outcomes in 2015 \$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.8: 2SLS (Overdentified): α (Tracts)

	(1)	(2)	(3)	(4)
	Pooled	25th Pctl (\$10k)	50th Pctl (\$10k)	75th Pctl (\$10k)
α	−1.164***	−0.341	0.065	0.531*
	(0.375)	(0.209)	(0.191)	(0.278)
Ln Total Pop.	0.032*	−0.016	−0.014	−0.011
	(0.018)	(0.010)	(0.009)	(0.012)
Female (%)	−0.685***	−0.299***	−0.465***	−0.647***
	(0.208)	(0.102)	(0.117)	(0.165)
White (%)	2.012***	1.111***	1.088***	1.092***
	(0.261)	(0.120)	(0.150)	(0.231)
Black (%)	0.199	−0.153	−0.525***	−0.990***
	(0.266)	(0.124)	(0.152)	(0.234)
Asian (%)	0.849**	0.704***	1.020***	1.394***

	(0.393)	(0.202)	(0.215)	(0.315)
Hispanic (%)	1.266***	0.842***	0.730***	0.609***
	(0.259)	(0.118)	(0.148)	(0.229)
<18 y.o. (%)	1.310***	0.505***	0.524***	0.543***
	(0.109)	(0.062)	(0.060)	(0.081)
Single Parent Families (%)	−1.675***	−0.847***	−0.879***	−0.966***
	(0.096)	(0.055)	(0.052)	(0.069)
Child w/ Parents (%)	0.107	0.023	0.147**	0.286***
	(0.106)	(0.059)	(0.061)	(0.075)
>1hr Commute (%)	0.457***	0.667***	0.484***	0.294***
	(0.106)	(0.055)	(0.054)	(0.074)
<20m Commute (%)	−0.094	−0.092***	0.008	0.129***
	(0.060)	(0.034)	(0.031)	(0.040)
Grad. or Bachelors (%)	1.297***	0.503***	0.464***	0.429***
	(0.057)	(0.034)	(0.033)	(0.046)
HS Drop (%)	−0.903***	−0.497***	−0.288***	−0.054
	(0.133)	(0.075)	(0.073)	(0.102)
<$15k (%)	0.090	0.134**	0.094*	0.052
	(0.102)	(0.058)	(0.057)	(0.076)
$35-75k (%)	0.541***	0.154***	0.130**	0.096
	(0.100)	(0.056)	(0.054)	(0.072)
>$125k (%)	3.197***	1.511***	1.346***	1.132***
	(0.163)	(0.092)	(0.089)	(0.125)

Poor Families (%)	-0.208^{***}	-0.021	-0.068	-0.108^{*}
	(0.080)	(0.045)	(0.044)	(0.062)
Foreign Born (%)	-0.343^{***}	-0.063^{*}	-0.154^{***}	-0.267^{***}
	(0.059)	(0.033)	(0.031)	(0.043)
Constant	3.518^{***}	2.887^{***}	3.454^{***}	4.064^{***}
	(0.342)	(0.178)	(0.192)	(0.276)
Observations	7152	7152	7152	7152
Adj. R^2	0.908	0.883	0.913	0.887
Cragg-Donald (F-Stat)	11.419	11.419	11.419	11.419
Hansen (J-Stat)	1.309	2.057	0.513	6.212

Covariates in 1990 \$, Outcomes in 2015 \$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Beta

Table D.9: 2SLS (Just Identified): β (Tracts)

	(1)	(2)	(3)	(4)
	Pooled	25th Pctl (\$10k)	50th Pctl (\$10k)	75th Pctl (\$10k)
β	-15.579^{*}	-4.765	0.991	7.664
	(9.071)	(3.503)	(2.589)	(5.433)
Ln Total Pop.	0.107	0.007	-0.019	-0.049
	(0.069)	(0.027)	(0.020)	(0.040)
Female (%)	-0.726^{**}	-0.313^{**}	-0.462^{***}	-0.623^{***}

	(0.350)	(0.129)	(0.124)	(0.240)
White (%)	1.309***	0.901***	1.130***	1.425***
	(0.322)	(0.136)	(0.156)	(0.266)
Black (%)	−0.016	−0.213*	−0.514***	−0.899***
	(0.273)	(0.112)	(0.142)	(0.246)
Asian (%)	−2.120	−0.212	1.214*	2.877**
	(2.119)	(0.832)	(0.627)	(1.283)
Hispanic (%)	0.635**	0.653***	0.768***	0.908***
	(0.305)	(0.127)	(0.151)	(0.259)
<18 y.o. (%)	0.930***	0.388***	0.548***	0.731***
	(0.306)	(0.123)	(0.092)	(0.178)
Single Parent Families (%)	−1.915***	−0.923***	−0.862***	−0.840***
	(0.281)	(0.113)	(0.085)	(0.163)
Child w/ Parents (%)	−0.115	−0.045	0.161**	0.395***
	(0.190)	(0.080)	(0.071)	(0.119)
>1hr Commute (%)	0.712***	0.744***	0.469***	0.172
	(0.178)	(0.073)	(0.060)	(0.107)
<20m Commute (%)	−0.175*	−0.116***	0.012	0.167***
	(0.091)	(0.038)	(0.029)	(0.048)
Grad. or Bachelors (%)	1.126***	0.451***	0.474***	0.510***
	(0.115)	(0.047)	(0.035)	(0.070)
HS Drop (%)	−2.007**	−0.839**	−0.215	0.501
	(0.841)	(0.327)	(0.244)	(0.505)

<$15k (%)	0.496	0.261*	0.066	−0.155
	(0.367)	(0.143)	(0.111)	(0.226)
$35-75k (%)	0.441**	0.121	0.138**	0.152
	(0.211)	(0.084)	(0.065)	(0.122)
>$125k (%)	3.560***	1.617***	1.326***	0.967***
	(0.197)	(0.074)	(0.061)	(0.118)
Poor Families (%)	−0.440**	−0.091	−0.053	0.005
	(0.183)	(0.073)	(0.059)	(0.115)
Foreign Born (%)	1.016	0.353	−0.241	−0.936*
	(0.814)	(0.314)	(0.233)	(0.490)
Constant	5.922***	3.630***	3.296***	2.860***
	(1.759)	(0.688)	(0.531)	(1.085)
Observations	7152	7152	7152	7152
Adj. R^2	0.710	0.818	0.910	0.784
Cragg-Donald (F-Stat)	3.259	3.259	3.259	3.259

Covariates in 1990 $, Outcomes in 2015 $

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.10: 2SLS (Overdentified): β (Tracts)

	(1) Pooled	(2) 25th Pctl ($10k)	(3) 50th Pctl ($10k)	(4) 75th Pctl ($10k)
β	−1.382	0.509	−0.498	−1.917

	(1.722)	(1.264)	(1.078)	(1.438)
Ln Total Pop.	0.006	−0.031***	−0.008	0.019
	(0.017)	(0.011)	(0.010)	(0.013)
Female (%)	−0.598***	−0.265**	−0.475***	−0.709***
	(0.201)	(0.105)	(0.113)	(0.144)
White (%)	1.645***	1.025***	1.095***	1.198***
	(0.185)	(0.101)	(0.144)	(0.217)
Black (%)	−0.190	−0.278***	−0.496***	−0.781***
	(0.173)	(0.092)	(0.137)	(0.210)
Asian (%)	1.158**	1.006***	0.870***	0.665
	(0.491)	(0.332)	(0.316)	(0.433)
Hispanic (%)	0.922***	0.760***	0.737***	0.714***
	(0.181)	(0.097)	(0.142)	(0.216)
<18 y.o. (%)	1.316***	0.532***	0.508***	0.471***
	(0.106)	(0.071)	(0.064)	(0.082)
Single Parent Families (%)	−1.494***	−0.767***	−0.906***	−1.124***
	(0.081)	(0.052)	(0.048)	(0.061)
Child w/ Parents (%)	0.082	0.028	0.140**	0.262***
	(0.102)	(0.061)	(0.062)	(0.078)
>1hr Commute (%)	0.571***	0.692***	0.484***	0.268***
	(0.094)	(0.055)	(0.053)	(0.069)
<20m Commute (%)	−0.164***	−0.112***	0.011	0.159***
	(0.050)	(0.031)	(0.029)	(0.036)

Grad. or Bachelors (%)	1.224***	0.488***	0.464***	0.445***
	(0.049)	(0.033)	(0.030)	(0.037)
HS Drop (%)	−0.704***	−0.354***	−0.351***	−0.379***
	(0.175)	(0.123)	(0.109)	(0.146)
<$15k (%)	−0.046	0.060	0.123**	0.211***
	(0.100)	(0.067)	(0.061)	(0.078)
$35-75k (%)	0.695***	0.215***	0.111**	−0.020
	(0.087)	(0.051)	(0.049)	(0.062)
>$125k (%)	3.579***	1.624***	1.324***	0.954***
	(0.104)	(0.063)	(0.057)	(0.068)
Poor Families (%)	−0.241***	−0.017	−0.074	−0.129**
	(0.077)	(0.048)	(0.046)	(0.062)
Foreign Born (%)	−0.249	−0.117	−0.108	−0.082
	(0.161)	(0.117)	(0.101)	(0.135)
Constant	3.181***	2.612***	3.583***	4.710***
	(0.426)	(0.287)	(0.268)	(0.358)
Observations	7152	7152	7152	7152
Adj. R^2	0.928	0.886	0.913	0.893
Cragg-Donald (F-Stat)	5.882	5.882	5.882	5.882
Hansen (J-Stat)	16.770	4.862	0.427	9.523

Covariates in 1990 $, Outcomes in 2015 $

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Tau

Table D.11: 2SLS (Just Identified): τ (Tracts)

	(1)	(2)	(3)	(4)
	Pooled	25th Pctl ($10k)	50th Pctl ($10k)	75th Pctl ($10k)
τ	-1.210^{***}	-0.370^{*}	0.077	0.595^{**}
	(0.408)	(0.214)	(0.196)	(0.301)
Ln Total Pop.	0.050^{**}	-0.011	-0.015	-0.021
	(0.024)	(0.013)	(0.011)	(0.016)
Female (%)	-0.764^{***}	-0.325^{***}	-0.459^{***}	-0.604^{***}
	(0.226)	(0.107)	(0.122)	(0.182)
White (%)	2.056^{***}	1.129^{***}	1.083^{***}	1.058^{***}
	(0.292)	(0.129)	(0.152)	(0.241)
Black (%)	0.319	-0.111	-0.536^{***}	-1.063^{***}
	(0.311)	(0.141)	(0.160)	(0.254)
Asian (%)	0.494	0.587^{**}	1.047^{***}	1.592^{***}
	(0.493)	(0.248)	(0.247)	(0.374)
Hispanic (%)	1.307^{***}	0.859^{***}	0.725^{***}	0.577^{**}
	(0.290)	(0.127)	(0.150)	(0.238)
<18 y.o. (%)	1.262^{***}	0.490^{***}	0.527^{***}	0.568^{***}
	(0.121)	(0.065)	(0.061)	(0.086)
Single Parent Families (%)	-1.735^{***}	-0.868^{***}	-0.873^{***}	-0.929^{***}
	(0.116)	(0.063)	(0.059)	(0.082)
Child w/ Parents (%)	0.112	0.025	0.146^{**}	0.283^{***}

	(0.109)	(0.059)	(0.061)	(0.076)
>1hr Commute (%)	0.397***	0.648***	0.489***	0.327***
	(0.120)	(0.060)	(0.057)	(0.083)
<20m Commute (%)	−0.112*	−0.096***	0.008	0.136***
	(0.062)	(0.033)	(0.030)	(0.039)
Grad. or Bachelors (%)	1.276***	0.497***	0.465***	0.437***
	(0.059)	(0.033)	(0.032)	(0.047)
HS Drop (%)	−1.091***	−0.558***	−0.273***	0.050
	(0.194)	(0.103)	(0.098)	(0.145)
<$15k (%)	0.159	0.158**	0.088	0.011
	(0.122)	(0.066)	(0.064)	(0.091)
$35-75k (%)	0.489***	0.136**	0.135**	0.128
	(0.116)	(0.062)	(0.058)	(0.083)
>$125k (%)	3.171***	1.498***	1.351***	1.158***
	(0.178)	(0.095)	(0.092)	(0.137)
Poor Families (%)	−0.252***	−0.034	−0.065	−0.087
	(0.086)	(0.046)	(0.045)	(0.065)
Foreign Born (%)	−0.165*	−0.008	−0.165***	−0.355***
	(0.091)	(0.049)	(0.045)	(0.068)
Constant	3.734***	2.961***	3.435***	3.936***
	(0.404)	(0.204)	(0.212)	(0.317)
Observations	7152	7152	7152	7152
Adj. R^2	0.897	0.880	0.912	0.878

Cragg-Donald (F-Stat)	13.818	13.818	13.818	13.818

Covariates in 1990 \$, Outcomes in 2015 \$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.12: 2SLS (Overdentified): τ (Tracts)

	(1) Pooled	(2) 25th Pctl (\$10k)	(3) 50th Pctl (\$10k)	(4) 75th Pctl (\$10k)
τ	-1.075^{***}	-0.289	0.044	0.419
	(0.388)	(0.206)	(0.186)	(0.270)
Ln Total Pop.	0.044^{*}	-0.014	-0.014	-0.013
	(0.022)	(0.012)	(0.011)	(0.014)
Female (%)	-0.745^{***}	-0.313^{***}	-0.464^{***}	-0.630^{***}
	(0.220)	(0.106)	(0.121)	(0.171)
White (%)	2.013^{***}	1.104^{***}	1.093^{***}	1.113^{***}
	(0.279)	(0.123)	(0.151)	(0.234)
Black (%)	0.260	-0.146	-0.521^{***}	-0.987^{***}
	(0.297)	(0.135)	(0.158)	(0.244)
Asian (%)	0.604	0.653^{***}	1.020^{***}	1.449^{***}
	(0.470)	(0.239)	(0.243)	(0.353)
Hispanic (%)	1.267^{***}	0.835^{***}	0.735^{***}	0.629^{***}
	(0.277)	(0.121)	(0.149)	(0.231)
<18 y.o. (%)	1.272^{***}	0.496^{***}	0.525^{***}	0.555^{***}

	(0.116)	(0.064)	(0.061)	(0.082)
Single Parent Families (%)	−1.704***	−0.849***	−0.881***	−0.970***
	(0.111)	(0.061)	(0.057)	(0.076)
Child w/ Parents (%)	0.111	0.024	0.147**	0.285***
	(0.107)	(0.059)	(0.061)	(0.075)
>1hr Commute (%)	0.415***	0.658***	0.485***	0.304***
	(0.116)	(0.058)	(0.057)	(0.079)
<20m Commute (%)	−0.118**	−0.100***	0.010	0.143***
	(0.060)	(0.032)	(0.030)	(0.038)
Grad. or Bachelors (%)	1.271***	0.494***	0.466***	0.443***
	(0.056)	(0.032)	(0.031)	(0.044)
HS Drop (%)	−1.034***	−0.524***	−0.287***	−0.024
	(0.184)	(0.100)	(0.094)	(0.132)
<$15k (%)	0.130	0.141**	0.095	0.048
	(0.117)	(0.064)	(0.062)	(0.084)
$35-75k (%)	0.514***	0.151**	0.128**	0.094
	(0.112)	(0.060)	(0.057)	(0.077)
>$125k (%)	3.217***	1.526***	1.340***	1.099***
	(0.171)	(0.093)	(0.089)	(0.125)
Poor Families (%)	−0.249***	−0.032	−0.066	−0.092
	(0.083)	(0.045)	(0.045)	(0.062)
Foreign Born (%)	−0.188**	−0.022	−0.160***	−0.325***
	(0.087)	(0.048)	(0.044)	(0.063)

Constant	3.643***	2.907***	3.458***	4.055***
	(0.390)	(0.200)	(0.208)	(0.301)
Observations	7152	7152	7152	7152
Adj. R^2	0.905	0.884	0.913	0.889
Cragg-Donald (F-Stat)	7.390	7.390	7.390	7.390
Hansen (J-Stat)	2.303	2.753	0.563	7.612

Covariates in 1990 $, Outcomes in 2015 $

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D.4 Causal Effect with Mediating Impacts

WRLURI

Table D.13: GSEM: 2nd Stage Given WRLURI

	(1) Ad.Inc./Rent	(2) Exp. per Cap. (P)	(3) Family H
WRLURI	−165.214***	55.146**	−0.107
	(60.492)	(22.176)	(0.094)
Ln Total Pop.	2.274	−0.601	0.017***
	(1.416)	(0.533)	(0.003)
Female (%)	−39.203*	15.445*	−0.087***
	(22.430)	(8.453)	(0.030)
White (%)	−31.303	8.693	−0.098***

	(22.953)	(8.698)	(0.035)
Black (%)	−40.234*	15.448*	−0.127***
	(23.504)	(8.908)	(0.037)
Asian (%)	−193.795***	57.502**	−0.031
	(68.811)	(25.488)	(0.107)
Hispanic (%)	−24.187	6.659	0.026
	(17.002)	(6.664)	(0.030)
<18 y.o. (%)	−29.561	7.282	−0.033
	(26.669)	(9.728)	(0.039)
Single Parent Families (%)	10.941	−9.454**	0.088***
	(12.936)	(4.794)	(0.021)
Child w/ Parents (%)	−27.025**	13.189***	−0.063***
	(13.598)	(5.096)	(0.022)
>1hr Commute (%)	18.090	−1.881	−0.039
	(16.857)	(6.255)	(0.029)
<20m Commute (%)	−13.987	9.371**	−0.090***
	(13.014)	(4.779)	(0.020)
Grad. or Bachelors (%)	−32.315**	16.822***	−0.028
	(13.647)	(5.131)	(0.021)
HS Drop (%)	−137.774**	57.645***	−0.189**
	(56.674)	(20.953)	(0.086)
<$15k (%)	2.575	2.191	−0.036**
	(9.786)	(3.692)	(0.016)

\$35-75k (%)	15.007	-8.904^{*}	0.000
	(12.147)	(4.545)	(0.021)
>\$125k (%)	50.263	-26.769^{**}	0.090^{*}
	(33.876)	(12.443)	(0.051)
Poor Families (%)	21.851^{*}	-7.817^{*}	0.025
	(12.367)	(4.666)	(0.021)
Foreign Born (%)	188.372^{**}	-77.920^{***}	0.012
	(79.723)	(29.292)	(0.127)
Constant	104.088^{***}	-23.334^{*}	0.925^{***}
	(37.443)	(13.960)	(0.066)
Observations	7152	7152	7152

Covariates in 1990 \$, Outcomes and Rents in 2015 \$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.14: GSEM: 3rd Stage Given WRLURI

	(1)	(2)	(3)	(4)
	Pooled	25th Pctl (\$10k)	50th Pctl (\$10k)	75th Pctl (\$10k)
Ad.Inc./Rent (\$, UA)	0.053^{***}	0.006	0.017^{*}	0.025^{**}
	(0.016)	(0.010)	(0.009)	(0.012)
Expenditures per Cap (P)	0.132^{***}	0.017	0.042^{*}	0.063^{**}
	(0.037)	(0.023)	(0.022)	(0.029)
Family H (% UA)	-14.376^{***}	-1.605	-4.250	-6.355

	(5.035)	(3.047)	(2.998)	(3.933)
Ln Total Pop.	0.201***	−0.004	0.048	0.095
	(0.075)	(0.045)	(0.044)	(0.058)
Female (%)	−1.781***	−0.411	−0.830***	−1.230***
	(0.464)	(0.273)	(0.275)	(0.360)
White (%)	0.809**	0.928***	0.854***	0.860***
	(0.377)	(0.221)	(0.241)	(0.331)
Black (%)	−1.913***	−0.462	−1.013***	−1.576***
	(0.615)	(0.368)	(0.375)	(0.500)
Asian (%)	3.784***	1.159**	1.687***	2.171***
	(0.790)	(0.476)	(0.483)	(0.648)
Hispanic (%)	1.746***	0.845***	0.986***	1.108***
	(0.313)	(0.184)	(0.211)	(0.300)
<18 y.o. (%)	1.530***	0.556***	0.579***	0.599***
	(0.102)	(0.065)	(0.064)	(0.081)
Single Parent Families (%)	0.457	−0.561	−0.310	−0.184
	(0.640)	(0.385)	(0.381)	(0.501)
Child w/ Parents (%)	−1.097***	−0.121	−0.219	−0.265
	(0.392)	(0.239)	(0.234)	(0.303)
>1hr Commute (%)	−0.733*	0.536**	0.087	−0.335
	(0.415)	(0.253)	(0.246)	(0.321)
<20m Commute (%)	−1.932***	−0.315	−0.525	−0.653
	(0.587)	(0.356)	(0.350)	(0.457)

Grad. or Bachelors (%)	0.330	0.368**	0.184	0.028
	(0.258)	(0.156)	(0.154)	(0.204)
HS Drop (%)	−3.535***	−0.757	−1.212**	−1.576**
	(0.930)	(0.561)	(0.552)	(0.724)
<$15k (%)	−1.029***	−0.027	−0.180	−0.297
	(0.268)	(0.161)	(0.160)	(0.214)
$35-75k (%)	1.088***	0.254***	0.240***	0.202**
	(0.129)	(0.077)	(0.076)	(0.096)
>$125k (%)	5.698***	1.875***	1.979***	1.958***
	(0.676)	(0.406)	(0.400)	(0.525)
Constant	13.747***	3.893*	6.659***	9.066***
	(3.893)	(2.356)	(2.317)	(3.035)
Observations	7152	7152	7152	7152

Covariates in 1990 $, Outcomes and Rents in 2015 $

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Alpha

Table D.15: GSEM: 2nd Stage Given α

	(1) Ad.Inc./Rent	(2) Exp. per Cap. (P)	(3) Family H
α	131.362***	−43.847***	0.085

	(32.309)	(10.272)	(0.065)
Ln Total Pop.	-3.136^{**}	1.204^{***}	0.014^{***}
	(1.231)	(0.410)	(0.004)
Female (%)	6.094	0.326	-0.057^{***}
	(12.257)	(3.921)	(0.021)
White (%)	-16.419	3.725	-0.088^{***}
	(14.554)	(3.968)	(0.026)
Black (%)	-30.116^{*}	12.070^{***}	-0.121^{***}
	(15.581)	(4.355)	(0.029)
Asian (%)	53.175^{**}	-24.933^{***}	0.130^{***}
	(22.619)	(6.817)	(0.048)
Hispanic (%)	-27.940^{*}	7.912^{**}	0.024
	(14.516)	(3.950)	(0.029)
<18 y.o. (%)	40.487^{***}	-16.100^{***}	0.013
	(6.765)	(2.312)	(0.016)
Single Parent Families (%)	2.054	-6.488^{***}	0.082^{***}
	(6.230)	(2.035)	(0.015)
Child w/ Parents (%)	6.932^{*}	1.855	-0.041^{***}
	(3.923)	(1.384)	(0.010)
>1hr Commute (%)	-7.826	6.769^{***}	-0.056^{***}
	(6.325)	(2.235)	(0.017)
<20m Commute (%)	12.103^{***}	0.662	-0.073^{***}
	(3.758)	(1.182)	(0.008)

Grad. or Bachelors (%)	-7.175^{*}	8.431^{***}	-0.012
	(4.164)	(1.485)	(0.009)
HS Drop (%)	52.414^{***}	-5.837^{*}	-0.065^{***}
	(9.942)	(3.194)	(0.024)
<\$15k (%)	-2.445	3.866^{*}	-0.039^{**}
	(6.967)	(2.306)	(0.016)
\$35-75k (%)	7.497	-6.398^{***}	-0.005
	(6.275)	(2.124)	(0.016)
>\$125k (%)	7.567	-12.518^{***}	0.062^{**}
	(12.254)	(4.019)	(0.025)
Poor Families (%)	-6.039	1.493	0.007
	(5.057)	(1.707)	(0.012)
Foreign Born (%)	-32.716^{***}	-4.124^{***}	-0.132^{***}
	(3.726)	(1.211)	(0.010)
Constant	-57.835^{***}	30.713^{***}	0.820^{***}
	(20.004)	(6.062)	(0.041)
Observations	7152	7152	7152

Covariates in 1990 \$, Outcomes and Rents in 2015 \$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.16: GSEM: 3rd Stage Given α

	(1)	(2)	(3)	(4)

	Pooled	25th Pctl ($10k)	50th Pctl ($10k)	75th Pctl ($10k)
Ad.Inc./Rent ($, UA)	0.053***	0.007	0.017*	0.026**
	(0.016)	(0.009)	(0.009)	(0.012)
Expenditures per Cap (P)	0.133***	0.018	0.043*	0.065**
	(0.037)	(0.022)	(0.022)	(0.029)
Family H (% UA)	−14.435***	−1.655	−4.315	−6.435
	(5.027)	(3.034)	(2.985)	(3.930)
Ln Total Pop.	0.202***	−0.003	0.050	0.096*
	(0.074)	(0.045)	(0.044)	(0.058)
Female (%)	−1.788***	−0.417	−0.838***	−1.240***
	(0.462)	(0.270)	(0.273)	(0.360)
White (%)	0.812**	0.930***	0.856***	0.863***
	(0.379)	(0.221)	(0.240)	(0.331)
Black (%)	−1.917***	−0.466	−1.017***	−1.581***
	(0.616)	(0.367)	(0.374)	(0.500)
Asian (%)	3.792***	1.165**	1.696***	2.181***
	(0.790)	(0.475)	(0.482)	(0.648)
Hispanic (%)	1.751***	0.849***	0.992***	1.116***
	(0.315)	(0.184)	(0.210)	(0.300)
<18 y.o. (%)	1.540***	0.564***	0.590***	0.613***
	(0.102)	(0.064)	(0.063)	(0.081)
Single Parent Families (%)	0.461	−0.557	−0.305	−0.178
	(0.639)	(0.383)	(0.379)	(0.501)

Child w/ Parents (%)	−1.101***	−0.125	−0.224	−0.271
	(0.390)	(0.237)	(0.232)	(0.303)
>1hr Commute (%)	−0.744*	0.526**	0.075	−0.350
	(0.414)	(0.252)	(0.245)	(0.320)
<20m Commute (%)	−1.936***	−0.319	−0.530	−0.659
	(0.587)	(0.354)	(0.348)	(0.457)
Grad. or Bachelors (%)	0.325	0.362**	0.178	0.020
	(0.259)	(0.156)	(0.154)	(0.204)
HS Drop (%)	−3.547***	−0.768	−1.226**	−1.593**
	(0.928)	(0.558)	(0.549)	(0.723)
<$15k (%)	−1.030***	−0.027	−0.181	−0.297
	(0.269)	(0.161)	(0.160)	(0.214)
$35-75k (%)	1.088***	0.253***	0.240***	0.202**
	(0.129)	(0.077)	(0.076)	(0.096)
>$125k (%)	5.701***	1.878***	1.983***	1.963***
	(0.675)	(0.404)	(0.399)	(0.525)
Constant	13.790***	3.929*	6.705***	9.124***
	(3.887)	(2.346)	(2.307)	(3.033)
Observations	7152	7152	7152	7152

Covariates in 1990 $, Outcomes and Rents in 2015 $

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Beta

Table D.17: GSEM: 2nd Stage Given β

	(1)	(2)	(3)
	Ad.Inc./Rent	Exp. per Cap. (P)	Family H
β	1703.469*	−568.592*	1.108
	(955.651)	(317.040)	(0.987)
Ln Total Pop.	−11.174	3.887*	0.008
	(7.110)	(2.362)	(0.008)
Female (%)	10.161	−1.032	−0.055*
	(36.210)	(11.810)	(0.029)
White (%)	61.594**	−22.314***	−0.038
	(26.354)	(8.347)	(0.030)
Black (%)	−5.254	3.772	−0.104***
	(21.485)	(6.650)	(0.022)
Asian (%)	375.570*	−132.544*	0.340
	(219.737)	(73.004)	(0.230)
Hispanic (%)	42.165*	−15.489**	0.069***
	(24.510)	(7.673)	(0.027)
<18 y.o. (%)	81.938***	−29.935***	0.040
	(30.605)	(10.211)	(0.033)
Single Parent Families (%)	27.529	−14.991	0.099***
	(27.927)	(9.317)	(0.031)
Child w/ Parents (%)	31.185*	−6.241	−0.025

	(17.344)	(5.793)	(0.018)
>1hr Commute (%)	-36.070^{**}	16.196^{***}	-0.074^{***}
	(16.389)	(5.468)	(0.018)
<20m Commute (%)	21.193^{**}	-2.372	-0.067^{***}
	(8.247)	(2.746)	(0.009)
Grad. or Bachelors (%)	11.674	2.140	0.000
	(11.435)	(3.903)	(0.012)
HS Drop (%)	171.979^{*}	-45.746	0.012
	(88.105)	(29.207)	(0.094)
<$15k (%)	-46.156	18.456	-0.068^{*}
	(38.446)	(12.777)	(0.040)
$35-75k (%)	17.811	-9.840	0.002
	(20.693)	(6.960)	(0.023)
>$125k (%)	-33.477^{*}	1.182	0.036^{**}
	(18.878)	(6.389)	(0.018)
Poor Families (%)	19.365	-6.987	0.023
	(18.624)	(6.168)	(0.020)
Foreign Born (%)	-181.187^{**}	45.433	-0.229^{***}
	(85.854)	(28.447)	(0.087)
Constant	-318.619^{*}	117.759^{*}	0.650^{***}
	(183.981)	(60.993)	(0.189)
Observations	7152	7152	7152

Covariates in 1990 $, Outcomes and Rents in 2015 $

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.18: GSEM: 3rd Stage Given β

	(1)	(2)	(3)	(4)
	Pooled	25th Pctl ($10k)	50th Pctl ($10k)	75th Pctl ($10k)
Ad.Inc./Rent ($, UA)	0.052***	0.006	0.016*	0.025**
	(0.016)	(0.010)	(0.009)	(0.012)
Expenditures per Cap (P)	0.130***	0.016	0.041*	0.064**
	(0.037)	(0.023)	(0.022)	(0.029)
Family H (% UA)	−14.221***	−1.536	−4.220	−6.364
	(5.062)	(3.048)	(2.995)	(3.934)
Ln Total Pop.	0.198***	−0.006	0.048	0.095
	(0.075)	(0.045)	(0.044)	(0.058)
Female (%)	−1.763***	−0.403	−0.827***	−1.231***
	(0.464)	(0.272)	(0.274)	(0.360)
White (%)	0.804**	0.925***	0.852***	0.860***
	(0.378)	(0.221)	(0.240)	(0.331)
Black (%)	−1.903***	−0.458	−1.011***	−1.577***
	(0.619)	(0.368)	(0.375)	(0.500)
Asian (%)	3.763***	1.150**	1.683***	2.172***
	(0.793)	(0.476)	(0.483)	(0.648)
Hispanic (%)	1.731***	0.838***	0.983***	1.109***

	(0.313)	(0.183)	(0.210)	(0.300)
<18 y.o. (%)	1.502***	0.544***	0.574***	0.601***
	(0.102)	(0.064)	(0.063)	(0.081)
Single Parent Families (%)	0.445	−0.566	−0.312	−0.183
	(0.643)	(0.385)	(0.381)	(0.501)
Child w/ Parents (%)	−1.084***	−0.116	−0.216	−0.265
	(0.393)	(0.238)	(0.233)	(0.303)
>1hr Commute (%)	−0.703*	0.549**	0.093	−0.336
	(0.417)	(0.253)	(0.246)	(0.321)
<20m Commute (%)	−1.921***	−0.311	−0.523	−0.654
	(0.591)	(0.356)	(0.350)	(0.457)
Grad. or Bachelors (%)	0.346	0.374**	0.187	0.027
	(0.260)	(0.157)	(0.154)	(0.204)
HS Drop (%)	−3.501***	−0.742	−1.206**	−1.578**
	(0.935)	(0.561)	(0.551)	(0.724)
<$15k (%)	−1.028***	−0.026	−0.180	−0.297
	(0.270)	(0.162)	(0.160)	(0.214)
$35-75k (%)	1.089***	0.254***	0.240***	0.202**
	(0.130)	(0.077)	(0.076)	(0.096)
>$125k (%)	5.688***	1.870***	1.977***	1.958***
	(0.680)	(0.406)	(0.400)	(0.526)
Constant	13.635***	3.844	6.636***	9.073***
	(3.913)	(2.357)	(2.314)	(3.036)

Observations	7152	7152	7152	7152

Covariates in 1990 \$, Outcomes and Rents in 2015 \$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Tau

Table D.19: GSEM: 2nd Stage Given τ

	(1) Ad.Inc./Rent	(2) Exp. per Cap. (P)	(3) Family H
τ	132.297***	−44.159***	0.086
	(37.439)	(12.060)	(0.066)
Ln Total Pop.	−4.982***	1.820***	0.012***
	(1.919)	(0.632)	(0.005)
Female (%)	14.415	−2.452	−0.052**
	(16.423)	(5.239)	(0.023)
White (%)	−20.014	4.925	−0.091***
	(18.358)	(5.133)	(0.028)
Black (%)	−41.865*	15.992**	−0.128***
	(21.363)	(6.240)	(0.034)
Asian (%)	89.782***	−37.152***	0.154**
	(34.686)	(10.792)	(0.063)
Hispanic (%)	−31.231*	9.010*	0.022
	(18.366)	(5.137)	(0.031)

<18 y.o. (%)	45.606***	−17.808***	0.016
	(8.391)	(2.790)	(0.017)
Single Parent Families (%)	7.833	−8.417***	0.086***
	(8.627)	(2.826)	(0.018)
Child w/ Parents (%)	6.352	2.048	−0.041***
	(4.709)	(1.618)	(0.010)
>1hr Commute (%)	−1.618	4.697	−0.052***
	(8.525)	(2.887)	(0.018)
<20m Commute (%)	14.283***	−0.065	−0.072***
	(4.080)	(1.292)	(0.008)
Grad. or Bachelors (%)	−4.666	7.594***	−0.010
	(4.632)	(1.624)	(0.008)
HS Drop (%)	71.870***	−12.331**	−0.053
	(16.486)	(5.331)	(0.033)
<$15k (%)	−9.308	6.157*	−0.044**
	(9.810)	(3.225)	(0.018)
$35-75k (%)	12.560	−8.088***	−0.001
	(8.461)	(2.839)	(0.018)
>$125k (%)	9.040	−13.010***	0.063**
	(14.705)	(4.839)	(0.026)
Poor Families (%)	−1.179	−0.129	0.010
	(6.062)	(1.994)	(0.013)
Foreign Born (%)	−52.048***	2.329	−0.144***

	(7.525)	(2.384)	(0.013)
Constant	-79.368^{***}	37.901^{***}	0.806^{***}
	(28.620)	(8.876)	(0.050)
Observations	7152	7152	7152

Covariates in 1990 \$, Outcomes and Rents in 2015 \$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table D.20: GSEM: 3rd Stage Given τ

	(1)	(2)	(3)	(4)
	Pooled	25th Pctl (\$10k)	50th Pctl (\$10k)	75th Pctl (\$10k)
Ad.Inc./Rent (\$, UA)	0.053^{***}	0.007	0.017^{*}	0.025^{**}
	(0.016)	(0.009)	(0.009)	(0.012)
Expenditures per Cap (P)	0.133^{***}	0.018	0.043^{*}	0.064^{**}
	(0.037)	(0.022)	(0.022)	(0.029)
Family H (% UA)	-14.414^{***}	-1.658	-4.312	-6.425
	(5.034)	(3.032)	(2.986)	(3.931)
Ln Total Pop.	0.201^{***}	-0.003	0.050	0.096^{*}
	(0.074)	(0.045)	(0.044)	(0.058)
Female (%)	-1.786^{***}	-0.417	-0.838^{***}	-1.239^{***}
	(0.462)	(0.270)	(0.273)	(0.360)
White (%)	0.811^{**}	0.930^{***}	0.856^{***}	0.863^{***}
	(0.380)	(0.222)	(0.241)	(0.331)

Black (%)	-1.916^{***}	-0.466	-1.017^{***}	-1.581^{***}
	(0.618)	(0.367)	(0.374)	(0.500)
Asian (%)	3.789^{***}	1.166^{**}	1.695^{***}	2.180^{***}
	(0.792)	(0.475)	(0.482)	(0.648)
Hispanic (%)	1.749^{***}	0.850^{***}	0.992^{***}	1.115^{***}
	(0.316)	(0.184)	(0.210)	(0.300)
<18 y.o. (%)	1.536^{***}	0.565^{***}	0.590^{***}	0.611^{***}
	(0.102)	(0.064)	(0.063)	(0.081)
Single Parent Families (%)	0.460	-0.557	-0.305	-0.179
	(0.640)	(0.383)	(0.380)	(0.501)
Child w/ Parents (%)	-1.100^{***}	-0.125	-0.224	-0.270
	(0.390)	(0.237)	(0.232)	(0.303)
>1hr Commute (%)	-0.740^{*}	0.525^{**}	0.075	-0.348
	(0.414)	(0.252)	(0.245)	(0.320)
<20m Commute (%)	-1.935^{***}	-0.319	-0.529	-0.658
	(0.588)	(0.354)	(0.348)	(0.457)
Grad. or Bachelors (%)	0.327	0.362^{**}	0.178	0.021
	(0.259)	(0.156)	(0.154)	(0.204)
HS Drop (%)	-3.543^{***}	-0.768	-1.226^{**}	-1.591^{**}
	(0.930)	(0.558)	(0.549)	(0.723)
<$15k (%)	-1.030^{***}	-0.027	-0.180	-0.297
	(0.269)	(0.161)	(0.160)	(0.214)
$35-75k (%)	1.088^{***}	0.253^{***}	0.240^{***}	0.202^{**}

	(0.129)	(0.077)	(0.076)	(0.096)
>\$125k (%)	5.700***	1.878***	1.983***	1.962***
	(0.676)	(0.404)	(0.399)	(0.525)
Constant	13.775***	3.932*	6.703***	9.116***
	(3.892)	(2.345)	(2.307)	(3.033)
Observations	7152	7152	7152	7152

Covariates in 1990 \$, Outcomes and Rents in 2015 \$

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$