Land Use Regulation and Housing Prices [*]

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Abstract

Land use regulations cause local housing supply restrictions and raise local housing prices, as shown in a large empirical literature. If supply is restricted by local regulation, it is likely to cause a spillover of demand and price effects in other localities. In this paper, we test for spillover price effects. We develop a general equilibrium model with household choice on consumption and location and local housing production with empirical implications for which we test. Using property transaction data from 1993 to 2017 in California and a regulatory index compiled from the Wharton Residential Land Use Survey (Gyourko, Saiz and Summers, 2008), we structurally estimate and identify the general equilibrium and partial equilibrium effects. We examine overall and within-MSA regulatory interdependence and find significant and positive spillover effects of regulation on housing prices. The existence of a general equilibrium effect mitigates the direct effect of local regulation on local housing prices.

Keywords: housing prices, land use regulation, general equilibrium, spillover effect, California
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1. Introduction

Local land use regulation's impact on housing prices is the subject of a large empirical literature. In addition, since the US Supreme case of Euclid v. Ambler (1926), land use regulation has been the subject of policy discussions on the role of zoning in excluding households from communities through housing affordability effects.[1] A separate conceptual literature has developed on the potential existence of monopoly zoning, which raises housing prices, as opposed to zoning that deflects repressed local demand to available housing in surrounding communities.[2] These strands of literature implicitly assume the existence of spillover effects of local regulation on nonlocal housing markets.

Higher housing prices pushed up by tighter regulation may incur housing demand reallocation from cities imposing land restrictions to neighboring cities and beyond; that is, land use regulation may cause spillover effects. Such spillover effects, in theory, could mitigate the impact of local regulation on housing prices, because they allow a reallocation of demand to surrounding communities. In the absence of such reallocation, price impacts of regulation in the home community would likely be larger.

Most studies in the empirical literature do not model such spillover effects. Rather empirical studies of the impact of land use regulation generally regress housing prices against a regulatory index, community by community, without separately considering regulatory impacts on prices that spillover across local borders. For example, in a recent study, Jackson (2018) uses a pooled sample of Zillow hedonic price indices for California cities over three years (2000, 2006, 2012) to determine the impact of regulation on local prices using a regulatory index constructed from the California Land Use Survey in 2018, and finds a 5% regulatory effect on housing prices. An earlier paper by Quigley, Raphael and Rosenthal (2008) on housing prices in 86 cities of the San Francisco Bay Area, using a similarly constructed regulatory index from the Berkeley Land Use Survey, finds a regulatory effect on housing prices of 1-2% based on OLS and 3.8%-5.3% when regulation is instrumented by political preference. We replicate these studies, but we also ask to what degree are these outcomes the result of a direct impact of local regulation and to what extent they are due to an indirect effect of a spillover effect of local demand redirected to surrounding communities. In so doing, we show the importance of the spatial context in which local regulation occurs for housing price outcomes.

We formalize the regulatory spillover effect through a general equilibrium model with household mobility. We include household decisions over location that respond to local regulation and the degree to which local regulation is more or less stringent than that of other localities. Tighter regulation in a locality is hypothesized to increase housing supply costs, leading to a leftward shift in the housing supply curve and higher housing prices, but the ultimate impact on prices depends on household

[1] The case of Village of Euclid, Ohio v. Ambler Realty Co. set the precedent of new zoning practice and served to bolster local zoning ordinances nationwide. For the details of Euclid v. Ambler, see Fluck (1986).

[2] See Quigley and Rosenthal (2005).

mobility and the choice set of localities with and without regulation. When we separate out the GE effect we show far larger double-digit effects for the impact of regulation on housing prices in the home community. Depending upon the general equilibrium effect, the same local regulatory action will have different impacts on local housing prices. Omitting the separate impact on surrounding communities underestimates the home regulatory effect on housing prices.

Our estimation relies on multiple data sources. We obtain housing price data for all residential transactions in California from 1993 to 2017 and additional local variables. We focus on 185 cities surveyed in California in the Wharton Land Use Survey (Gyourko, Saiz and Summers, 2008), covering 5 million transactions. Per capita income data comes from the regional/MSA dataset from Moody's Analytics. We also instrument per capita income with demographic variables (mean household age, share of high education and share of high-tech jobs) from the American Community Survey. We control for macro conditions (mortgage credit growth, 30-year FRM rate) to improve the goodness of fit along the time-series dimension.

The paper is organized as follows. Section 2 reviews the literature. Section 3 sets up a general equilibrium model of regulation and housing markets. Section 4 describes the data and summary statistics. Section 5 maps the model to the structural estimation. Section 6 decomposes the regulatory effect into the partial equilibrium and general equilibrium effects. Section 7 estimates the intra-metro spillover effects, followed by the conclusion in Section 8.

2. Literature Review

The theoretical literature on regulation points to how local land use regulation may raise housing prices. Brueckner (1995) lays out a basic model in which local land use regulation restricts supply and increases the cost of housing. Quigley and Rosenthal (2005) provides a review of the empirical literature through 2005 quantifying these potential effects. We update this review with a summary of relevant empirical studies in Table 1. While data and methods vary and results are not directly comparable, there is a remarkable convergence on the estimated effect of regulation on prices in these studies. The studies, for the US (Huang and Tang, 2012), Boston (Glaeser and Ward, 2009), Florida (Ihlanfeldt, 2007), and California (Quigley and Raphael, 2005; Quigley et al, 2008; Kok et al, 2014; Jackson, 2018), include housing prices as the independent variable with explanatory variables including controls (*e.g.* housing and neighborhood characteristics) and survey-based measurements of local regulation. Most employ OLS estimations, while Ihlanfeldt (2007) instruments regulation using jurisdictional variables and Quigley et al. (2008) does so through political preference measurements, finding larger impacts for the endogenized measures of regulation (as shown in Table 1). To construct measures of local land use regulation, most of the studies use surveys with sub-indices (e.g. on approval delays or open space requirements) and either implement a standardized sum of regulations (Quigley and Raphael, 2005; Ihlanfeldt, 2007; Glaeser and Ward, 2009; Kok et al, 2014; Jackson, 2018), or principal factor analysis (Quigley et al, 2008; Huang and Tang, 2012). Across studies the impact of a standard deviation change in regulation on housing prices is generally estimated to be around 5%, with the exception of Glaeser and Ward's study on Boston metro from 2000 to 2005which finds a 10% impact on housing prices.

Such studies rely on locally fielded surveys. The first such index, the Wharton Survey of Planning and Policy, was constructed by Linneman, Summers, Brooks and Buist in 1990 followed on by a survey done for California (Glickfeld and Levine, 1992). In 2008, Quigley, Raphael and Rosenthal developed the Berkeley Land Use Survey, for 86 cities in the San Francisco Bay Area. Most recently, Jackson (2018) administered the California Land Use Survey (CaLURI) for 252 cities in California. The index we use is based on the Wharton Residential Land Use Regulation Index (WRLURI) which was compiled for the US (Gyourko, Saiz and Summers, 2008) in a similar fashion to the CaLURI index.[3] WRLURI is a national survey with responses from 2,649 jurisdictions and its measured value by locality is based on a principal factor analysis of sub-indices which is used to construct a single regulatory index measure for each reporting locality.[4] While it is possible to use such surveys to develop relative indexes of regulation and to ask the question of whether a locality that adopts a regulatory index that is more stringent than its neighbors causes demand to spillover to neighboring jurisdiction, these indexes have not been generally used to this end.

The conceptual literature shows that not all price effects that occur through zoning are local (Fischel, 1987; Rose, 1989; Bates, 1993; Thorson, 1996). Spatial spillover effects may extend beyond the locality that imposes the regulation, if localities drive up their own prices through "monopoly" zoning and drive out potential residents due to higher prices. The literature points to the restrictive effect as likely to induce spillover to neighboring markets, although amenity effects may also cause spillover if the lack of affordable housing in amenity-rich localities constrains choice. Pollakowski and Wachter (1990) shows how the existence of a spillover effect on prices from a highly regulated locality to a less regulated neighboring locality within a region may demonstrate the existence of a restrictive effect on housing supply.[5] If such effects exist, pricing outcomes in the home community may depend not only

[3] See Gyourko and Malloy (2015) for a comparative discussion of these indices.

[4] Many subsequent studies use the Wharton Land Use Survey. Saiz (2010) estimates the housing supply elasticity as a function of physical constraints and regulatory measures from the Wharton survey. Turner, Haughwout and Van Der Klaauw (2014) uses the Wharton survey to identify the local regulatory effect on the land transaction prices at the boundaries of adjacent jurisdictions with different regulation. Quigley, Raphael and Rosenthal (2008) uses the Wharton survey instruments that are adapted to California to study the housing markets in the San Francisco Bay Area.

[5] Pollakowski and Wachter (1990), Brueckner (1990), and Engle, Navarro and Carson (1992) discuss a separate so-called amenity channel in which housing prices may rise due to quality of life effects of regulation in the home community. Quigley and Rosenthal (2005) summarizes the empirical literature and finds that supply effects dominate. Fischel (1990) discusses the interplay of both of these effects on housing prices and the difficulty of separately identifying their impacts. We also separately measure these home price effects in the appendix and find a relatively small amenity effect which

on their home community regulation but that of neighboring communities as well. Tighter growth controls in the neighboring area may increase the home locality's pricing power. If so, the same level of regulation may have different outcomes over space and over time depending on regulation in surrounding localities. In the following section, using a general equilibrium approach, we develop a spatial model to measure this effect.[6]

3. Model

We set up a spatial general equilibrium model with households who choose where to locate and housing suppliers whose costs will vary with local regulation. We solve for the equilibrium housing price as a function of land use regulation and income and identify price effects on the home market and surrounding markets. In so doing we show how the existence of substitute surrounding markets lessens the partial equilibrium impact of regulation on home housing prices through a general equilibrium effect.

Figure 1 illustrates this. Starting from an initial equilibrium denoted by E_0, land use regulation tightens in Market 1 and remains unchanged in Market 2. The tighter land use regulation in Market 1 is shown by a leftward shift in the supply curve. Tighter regulation pushes up housing prices in Market 1 to a partial equilibrium denoted by $E_{1,}$ due to the supply curve shift. The change of housing price in Market 1 incurs reallocation of housing demand between two markets, leading to a leftward shift in the demand curve in Market 1 and a rightward shift in the demand curve or a spillover effect in Market 2. Eventually, both housing markets will settle at the new equilibrium denoted by E_2.

3.1 Household Problem

Households indexed by *i* value the non-durable consumption *c* and housing consumption *h*. We assume that the household's preference has a Cobb-Douglas form. A household makes two sets of choices on consumption and location. Given city *j* location and housing price p_j, household *i* solves the standard consumption choice problem.[7]

$$v_j^i(p_j) = \max_{c,h} (1-\alpha)\ln c + \alpha \ln h + \beta_{ij} \quad s.t.\ \ p_j h + c \le Y_i Z_j A_j, \text{ where } A_j = Z_j^{\phi-1} \quad (1)$$

does not change the main results. We interpret the general equilibrium effects as occurring through affordability decreases occurring along with relative price rises, both of which may lead to spillover effects.

[6] Spatial equilibrium models in urban economics date back to the pioneering work by Rosen (1979) and Roback (1982) and is extended by Glaeser and Gottlieb (2009).

[7] We assume that the expenditure on housing consumption is linear in the housing rent. There are models in the literature with non-linear pricing to take into account housing quality (Landvoigt, Piazzesi and Schneider, 2015). We make the assumption, not only because linear pricing is simple and tractable for analysis, but also because we are able to use the residential transaction data with detailed structural characteristics to control housing quality in the model estimation.

The indirect utility of household i in city j can be written as a function of housing price p_j. To incorporate specific non-linearity effects that are a function of local income and to extend the income elasticity of housing demand to be greater or less than one, we include an idiosyncratic household income Y_i, a city-specific income Z_j, and a demand shifter A_j.[8] The demand shifter A_j may be associated with amenity effects and agglomeration effects in a reduced form. We assume two income components, Y_i and Z_j, are independently distributed and are multiplicative for tractability of analysis.[9] We assume A_j is a function of city income Z_j. The parameter ϕ controls the income elasticity. If $\phi > 1$, the shifter increases with city income. The parameter α measures the share of housing consumption relative to non-durable consumption in total expenditure. The city utility flow to an individual household is denoted by β_{ij}; this captures personal preference of location and any hidden benefit unobservable to econometricians. Conditional on living in city j, the household housing demand and the indirect utility function are

$$h_{ij}^D(p_j) = \alpha Y_i Z_j^{\phi}/p_j \tag{2}$$

$$v_j^i(p_j) = \alpha \ln \alpha + (1-\alpha)\ln(1-\alpha) - \alpha \ln p_j + y_i + \phi z_j + \beta_{ij} \tag{3}$$

where $y_i = \ln(Y_i)$ and $z_j = \ln(Z_j)$. The location choice of household i is thus a discrete choice problem. If household i moves to the city j instead of an alternative city k in the choice set, then the household utility in the city j must yield the highest value.

$$v_j^i(p_j) \geq \max_{k \neq j} v_k^i(p_k) \tag{4}$$

We assume that β_{ij} is identically and independently Type-I Extreme-Value distributed across cities. That is, when a household makes a location choice, they can make the decision based on city income, the price of housing and a private utility flow β_{ij} of city j.[10] The share of households located in city j is thus as follows.

$$q_j(p) = \frac{Z_j^{\phi} p_j^{-\alpha}}{\sum_{k \in S} Z_k^{\phi} p_k^{-\alpha}},\ p = \{p_k\}_{k \in S} \tag{5}$$

We can interpret the share as a standardized city index that households create to make location choices based on income and housing prices. As the number of households is normalized to unity, the share of household in city j coincides with the moving probability of a household to city j.

3.2 Housing Developer Problem

In each city, we assume there is a local housing developer who operates a production technology using land L as the input. The housing developer pays a marginal housing supply cost c_j for each unit of land.

[8] We incorporate the demand shifter in the model as a multiplier of the household income. With log preference, it is equivalent to a model where a city-specific utility flow $\ln(A_j)$ is added to the household utility.

[9] The assumption simplifies the aggregation of individual housing demand to the housing demand in each city.

[10] The difference $\beta_{ij} - \beta_{ik}$ has a Logit distribution, because the private utility flow is Type-I Extreme-Value distributed.

The marginal cost c_j includes the construction cost of materials and labor c_0 (constant across cities) and the city-specific costs related to land use regulation. The housing developer in city j solves the following profit maximization problem.

$$\max_{L,H}\ p_j H - c_j L \quad s.t.\ H = A_0 L^{\theta},\ c_j = \tau_j c_0 \tag{6}$$

where $A_0 > 0$ is the aggregate productivity and $\theta < 1$ controls for the curvature of the production technology. We proceed with the assumption of the decreasing returns to scale technology, because it provides a straightforward way to motivate an upward sloping housing supply curve and to relate regulation to housing supply.[11] The parameter $\tau_j > 0$ measures the intensity of land use regulation. The more regulated the land use in city j is, the higher τ_j will be. Concretely, the parameter τ_j takes into account the time length of permit approval, density and supply restriction, the open space requirement etc. Hence, the regulation intensity τ_j can be interpreted as an aggregate of several regulatory factors.

$$\tau_j = \prod_s (\tau_j^s)^{\rho_s} \tag{7}$$

where τ_j^s is an underlying factor and $\rho_s > 0$ is the corresponding factor weight.[12] Hence, the housing supply curve is:

$$H_j^S(p_j) = A_0^{\frac{1}{1-\theta}} \left(\frac{\theta p_j}{c_j} \right)^{\frac{\theta}{1-\theta}} \tag{8}$$

3.3 Equilibrium Conditions and Housing Prices

There are two equilibrium conditions needed to satisfy the model. First, each household with random utility flow unobservable to econometricians should move to the city delivering the highest utility which determines the moving probability $q_j(p)$. Second, the housing price of each city is endogenous. We clear the housing markets in all cities and solve the prices simultaneously. The market clearing condition (9) requires that we equate housing demand by aggregating individual demand (2) to housing supply (8) within each city.

[11] As to the micro foundation of the assumption on the production technology, the model setup is isomorphic to a model with an urban planner in each city who operates a continuum of housing developers with idiosyncratic productivity. Consider there is a continuum of housing supplier indexed by ι. The index denotes the technology of a housing supplier ι who can produce is $\theta\iota^{\theta-1}$ for each unit of land. The smaller the index is, the more efficient a housing supplier is. The assumption is that a housing supplier can use at most 1 unit of land. An urban planner will rank the housing suppliers from the most to the least efficient first and decides how many of the top housing suppliers to operate. The urban planner needs to solve the following problem, which leads to the same optimality condition

$$\max_{L_j} \int_0^{L_j} \theta\iota^{\theta-1} d\iota - c_j \int_0^{L_j} 1 d\iota$$

[12] We assume the relationship between the unidimensional measure and the underlying factors of land use regulation follows a product form. The log form of equation (7) will correspond to the predicted score regression in the principal factor analysis that we use to construct a unidimensional index from multiple measures of land use regulation.

$$q_j(p)\int h_{ij}^D(p_j)di = H_j^S(p_j),\ \forall j \in S \tag{9}$$

The housing demand in city j is thus the product of the moving probability q_j and the expected individual demand in city j.[13] The equilibrium condition says that with household mobility, housing markets are inter-related. The market clearing condition of city j depends on the housing prices elsewhere, because households are free to move, based on city income and housing prices. The impact of regulation will thus spill over to other cities due to household's location choices being determined by local and non-local housing prices and income.

In the following analysis, we proceed with the case where n = 2. That is, for an arbitrary city j, there is a single outside moving option. However, we show in the appendix that for an arbitrary number of city options $n \geq 2$, there exists a unique set of moving probabilities and housing prices that clear the housing markets simultaneously in n cities.[14] We solve for the log housing prices $\ln(p_j)$ in closed form, as follows.[15]

$$\begin{aligned} \ln p_j &= [\theta \ln c_0 + \theta \ln \tau_j] - (1-\theta)\ln\left[1 + e^{(2\lambda-1)\phi(z_j - z_k) + \frac{\theta}{1-\theta}\lambda(\ln\tau_j - \ln\tau_k)}\right] \\ &\quad + [(1-\theta)(\ln Y_0 + \phi z_j) - \ln A_0] + [(1-\theta)\ln\alpha - \theta\ln\theta] \end{aligned} \tag{10}$$

The first two terms in the housing price equation are a function of regulation. The first term is the direct or partial equilibrium (PE) effect through the production channel. Tighter regulation will increase housing supply cost, leading to a leftward shift in the housing supply curve and an increase in housing prices. The second term is non-linear, taking into account the second-order feedback effect through the general equilibrium (GE) channel. The level of housing prices in city j depends positively on the impact of regulation in the neighboring city, *i.e.* the outside moving option.[16] Linearizing the second term in (10) results in the following housing price equation.[17]

$$\ln p_j = \theta(1-\tfrac{1}{2}\lambda)\ln\tau_j + (1-\theta)(\tfrac{3}{2}-\lambda)\phi z_j + \tfrac{1}{2}\theta\lambda\ln\tau_k + \tfrac{1}{2}(1-\theta)(2\lambda-1)\phi z_k + \beta_0 \tag{11}$$

where β_0 is a constant term. This housing price equation will be mapped to a testable model in the empirical analysis.

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[13] Because Y_i and Z_j are assumed independently distributed, we can integrate over the household demand and get the housing demand in city j. Because the individual housing demand is linear in Y_i, only the first moment is needed for aggregation.

[14] As there is no analytical form in general, the assumption of single outside moving option will allow us to derive a closed-form housing price equation.

[15] See the appendix for the derivation of the housing price equation.

[16] Higher income in the neighboring city will increase the housing prices in the neighboring city due to a rightward shift in the demand curve. Higher neighboring housing prices will trigger the general equilibrium effect and a rightward shift in the demand curve in the home city. We thus have a positive impact of neighboring income on the home housing prices.

[17] The second term in (10) formalizes the regulatory spillover effect from Pollakowski and Wachter (1990), modeled as a consequence of household mobility. In the Appendix, we show the details of linearization.

4. Data

We use multiple sources of data. The land use regulation data is from the Wharton residential land use regulation survey. The housing data come from the Zillow Transaction and Assessment Dataset. The regional data is based on the dataset compiled by Moody Analytics and American Community Survey.

4.1 Land Use Regulation Data

To measure the land use regulation in the data, we rely on the sub-indices underlying the Wharton Residential Land Use Regulation Index (WRLURI) from Gyourko, Saiz and Summers (2008).[18] The Wharton survey is a cross-sectional survey and WRLURI is estimated at the jurisdiction levels (cities hereafter). The questionnaires are sent to local administrative offices for voluntary response, so the response rate in some metro areas are lower than 50%.

We focus on the cities in California that are covered by WRLURI, because the quality of land use regulation data and the housing data in California is much better than that in other states.[19] Moreover, jurisdictions in California appear to vary greatly in their degree of land use regulation, creating sufficient variations of regulatory stringency (Fischel, 1995).

Throughout our analysis, we make the assumption that land use regulation is constant over time although we will test for this assumption as later data become available.[20] Land use surveys are not conducted frequently. Before Gyourko et al (2008), the most recent comprehensive land use survey that covers California is Glickfeld and Levine (1992).

There are 185 cities in California that responded to the Wharton Land Use Survey. While WRLURI covers only a limited number of jurisdictions (Turner, Haughwout and Van Der Klaauw, 2014), the survey data covers 43 out of 103 principal cities marked by the Census Bureau, including the top 6 cities measured by population in California (Los Angeles, San Diego, San Jose, San Francisco, Long Beach and Fresno).[21] The survey topics range from zoning and project approval to supply and density restriction that are aggregated into 11 sub-indices as the bases of WRLURI. We thus use 8 sub-indices that have cross-city variation to construct a unidimensional measure of regulation intensity, including the local political pressure index (LPPI), local zoning approval index (LZAI), local project approval

[18] Data on WRLURI is available online (http://real.wharton.upenn.edu/~gyourko/landusesurvey.html).

[19] The number of cities covered by the land use regulation survey in California is the second highest among all states, only 2 cities fewer than the top state which is Pennsylvania. The housing data discussed below has more comprehensive coverage and longer time length in California than in other states.

[20] A more recent wave of the Wharton survey will be available in late 2019.

[21] The principal cities within metropolitan and micropolitan statistical areas uses the 2006 US Census definition to align with the survey year. The ranking of the city population in California comes from US Census. For the number of principal cities covered by each metro area, see the appendix table.

index (LPAI), density restriction index (DRI), open space index (OSI), exactions index (EI), supply restriction index (SRI), approval delay index (ADI).[22]

Similar to Gyourko et al (2008), we apply a principal factor analysis to the 8 sub-indices above and define the predicted score of the first factor as the measure of land use regulation intensity. We derive and normalize the score to zero mean and unit variance and define the standardized value as the California Land Use Regulation Index (CALURI). The model counterparts of regulation are $\ln(\tau_j)$ for CALURI and $\ln(\tau_j^s)$ for the sub-index s.

In Figure 2, we show the spatial distribution of regulation indices in California across 185 cities. Noticeably, several cities within Los Angeles-Long Beach-Anaheim Metropolitan Statistical Area are highly ranked in terms of regulation intensity. In Figure 3, we show the kernel density of CALURI and WALURI in California. Compared with the standard normal density, the distribution of CALURI is more concentrated near the mean. CALURI has a fat right tail, indicating a non-trivial number of highly regulated cities. WALURI lies to the right of CALURI, meaning that cities in California are more regulated than the US average. In the appendix, we list the estimated CALURI by MSA and city. In Figure 4, we compare CALURI with WRLURI. We show that CALURI is highly positively correlated with WRLURI and the simple sum of the 8 sub-indices underlying CALURI, so the method of constructing the regulatory index is not driving the unidimensional measure of regulation intensity.

Throughout our study, we use CALURI instead of the sub-indices. Compared to the individual sub-indices that are sparsely distributed (as is shown in the appendix), CALURI provides a smooth and unimodal measure of regulation, making the estimation of a marginal effect of regulation possible.

4.2 Housing Data

For the housing data, we rely on the Zillow Transaction and Assessment Dataset (ZTRAX).[23] The entire ZTRAX dataset contains more than 400 million public records from across the US and includes information on deed transfers, mortgages, property characteristics, and geographic information for residential and commercial properties.

Particularly, we are interested in the transaction prices in the deed transfers and the housing characteristics in property assessment data in California. We restrict the data to observations with non-foreclosed sales of residential properties that have detailed documentation of housing characteristics. We use the following housing characteristics: the transaction date, the property use, the number of

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[22] The three sub-indices for dropout are the state political involvement index (SPII), the state court involvement index (SCII), and local assembly index (LAI) that is available only in New England. For the definitions of the sub-indices, see Gyourko et al (2008).

[23] More information on accessing the data can be found at www.zillow.com/research/ztrax/. ZTRAX database is provided by the Zillow Group. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group or any of its affiliates.

bedrooms, the number of bathrooms, the age of the property, the property size and the distance to the nearest core cities. We encode the age of the property, the property size and the distance to the nearest core cities that are not directly observable in ZTRAX. The age of the property is calculated as the difference of the transaction year and the built year. There are multiple fields measuring different aspects of the size of a property, so we define the maximum value in those fields as the property size. For properties located in a city in a Core-Based Statistical Area (CBSA), we calculate the great-circle distance in miles to the center of the leading principal city listed in the name of a CBSA. If there are multiple leading principal cities in the CBSA title, we use the distance to the center of the nearest leading principal cities. Other housing characteristics are available in ZTRAX, but they are either optionally reported or sparsely populated. The details of data filtering and construction of variables are documented in the appendix. We use the city name of a sales transaction as the key to match ZTRAX to the land use data. 184 out of 185 cities responded to the Wharton survey have at least one transaction record in ZTRAX (with Crescent City as the exception).

4.3 Regional data

We calculate gross domestic products (GDP) per capita based on data from Moody's Analytics. Moody Analytics compiles GDP for 402 US metropolitan statistical areas or metropolitan divisions from Current Employment Statistics, Bureau of Economic Analysis and County Business Patterns, and collect data on the metropolitan population from US Census Bureau. Both GDP and population data are annual. Ideally, we would use city-level income and population. We use the MSA-level data instead, because the series of city-level data are not available in general and are not long enough to cover the time periods in our data sample (Moody Analytics only covers the income and the population in the metropolitan statistical areas instead of micropolitan statistical areas).[24] 179 out of 185 cities responded to the Wharton Land Use Survey are matched to an MSA in Moody's data.[25]

To account for possible endogeneity of GDP per capita, we additionally collect other regional data as instrumental variables. The lag term of the log GDP per capita is a natural instrumental variable. In addition, we have three candidate instrumental variables on MSA demographics: the share of high education including college and graduate education for at least one year, the age of the population, and the share of high-tech jobs. Data on the share of high education and the average age of the population

[24] Moody's data at the MSA level traces back to 1990 and allow us to use observations from all sample years in ZTRAX Also those metropolitan statistical areas, by definition, are socioeconomically tied to the principal cities by commuting. Although land use regulation is local, growth is regional (Glickfeld and Levine, 1992; Quigley and Rosenthal, 2005; Quigley and Swoboda, 2007).

[25] 6 cities we drop in the analysis fall into 6 micropolitan statistical areas. They are: Fortuna city in Eureka-Arcata-Fortuna, μMSA; Lakeport City in Clearlake, μMSA; Susanville City in Susanville, μMSA; Ukiah City in Ukiah, μMSA; Corning City in Red Bluff, μMSA; Crescent City in Crescent City, μMSA.

come from the American Community Survey (ACS) Micro data from IPUMS USA.[26] Data on the share of high-tech jobs from 1990 to 2017 are compiled by Moody's Analytics, based on Bureau of Labor Statistics and Bureau of Economic Analysis.[27]

Besides per capita income, we include two additional regional controls. The first one is the air quality data at the MSA level from 1993 to 2017 from the Environment Protection Agency (EPA). EPA classifies each day into one of the seven groups (Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, Hazardous). We use the number of good days (out of 365 days) as our measure of air quality, because this measure is easy to interpret.[28] Moreover, the number of days with good air quality is a compound measure highly correlated with other air quality measures (the median or maximum Air Quality Index (AQI) in a year, days with NO_2, days with PM 2.5 etc.). The second regional control is the distance to the Pacific coast. We geocode the mile distance from the centroid of each city to the nearest Pacific coast to measure the California coastal effect.

4.4 Macroeconomic data

In addition, we control for variables related to macroeconomic conditions. The data covers the period that witnesses the strong boom and bust in residential mortgage and housing prices from 2001 to 2007 in California (Choi, Hong, Kubik, and Thompson, 2016). The time series variation of housing prices may heavily depend on lending conditions. We take this concern into account by introducing two macro variables: the growth rate of household mortgages in the US and the US 30-year average fixed-rate mortgage rate. Higher growth rate of mortgage lending is expected to increase housing demand by easing household borrowing, while a lower mortgage rate achieves the same effect by making borrowing cheaper.

In Figure 5, we show the time paths of the macro variables. We collect the data on the US household mortgage debt from Z.1 Financial Account Table from the Board of Governor of Federal Reserves and calculate the annual growth rate. The data on US 30-Year average fixed-rate mortgage rate comes from Primary Mortgage Market Survey by Freddie Mac.

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[26] Because ACS data starts from 2000, we fit the time trend and extrapolate the data for each MSA before 2000.

[27] High-tech jobs are defined from the following NAICS industries (NAICS code): Pharmaceutical and Medicine Manufacturing (3254), Computer and Peripheral Equipment Manufacturing (3341), Communications Equipment Manufacturing (3342), Semiconductor and Other Electronic Component Manufacturing (3344), Navigational, Measuring, Electromedical, and Control Instruments Manufacturing (3345), Medical Equipment and Supplies Manufacturing (3391), Software Publishers (5112), Wired Telecommunications Carriers (5171), Wireless Telecommunications Carriers (except Satellite) (5172), Satellite Telecommunications (5174), Other Telecommunications (5179), Other Information Services (5191), Data Processing, Hosting, and Related Services (5182), Computer Systems Design and Related Services (5415), Scientific Research and Development Services (5417), Other Professional, Scientific, and Technical Services (5419), Medical and Diagnostic Laboratories (6215)

[28] For earlier years and MSAs without daily observations, we calculate the share of good days in the total number of observed days and multiply the share by 365.

4.5 Summary Statistics

In Table 2, we show the geographical coverage of the matched land use sample of property transactions in 179 cities. Property sales in 963 cities are not matched to a city in the land use regulation data, but the matched sample covers 5.3 million residential transactions in 39 out of 58 California counties and 25 out of 26 metropolitan statistical areas in California from 1993 to 2017 in ZTRAX.

In Table 3, we report the summary statistics of CALURI, together with the 8 underlying sub-indices and WRLURI originally estimated by Gyourko, Saiz and Summers (2008). The city-level regulation indices are weighted by the number of property transactions in the cities. CALURI has a positive mean 0.27, a median -0.01, and a standard deviation 1.23. Because CALURI is normalized to zero mean and unit variance, the weighted statistics are consequences of the property transactions concentrated in more regulated and more populated cities in our sample.

In Table 4, we show the distribution of residential property uses. 76% of the property transactions are single-family residential, followed by 21% of condominium transactions. Compared with the distribution of the unmatched sample, we have a lower share of single-family units and a higher share of condominiums in the land use sample (84% and 13% in the unmatched sample respectively).

In Table 5, we report the summary statistics of the housing characteristics we control in the empirical analysis. The sales prices have been inflation adjusted to 2006. The average sales price is $370,000 dollars. The average size of a residential property is 1,700 square feet. We also show the sales price per square foot mean and median as $221 and $181. The average age of a residential property is 30 years. There are 2 bathrooms and 3 bedrooms on average in a residential property. The mean and the median distance of a property to the nearest core city in a metropolitan statistical area is 28 miles and 8 miles, respectively.[29]

In Table 6, we show summary statistics of the instrumental variables. The average share of high education is 36% in an MSA, while 6.84% of the total employment are high-tech jobs. The average age of an individual is 35 years ago. In Table 7, we report the correlation of the real GDP per capita with its lag term and 3 demographic instrumental variables, 0.99, while its correlation with the share of the share of high education, the population age, and the share of high-tech job 0.823, 0.753 and 0.651, respectively.

[29] Compared with the unmatched sample, the average property in the land use sample is more expensive in terms of the sales price per square foot and is smaller in size. It has slightly older age and a shorter distance to the nearest core cities. The number of bath rooms and bedrooms are close in the matched and unmatched samples.

5. Structural Estimation and Results

5.1 Estimation Method

To derive our empirical model, we make one additional assumption on the linearized housing price equation (11). We assume that the outside moving option of an arbitrary city *j*, called city *k*, is interpreted as a city with average income and regulation. The assumption further simplifies the regulatory index ($CALURI_k = 0$) and income ($z_k = \mathrm{E}_j[z_j]$) in city *k*. The assumption serves to mitigate the survey bias due to low response rate by relying less on the spatial information in estimation. Later, we will consider relaxing the assumption. We substitute for the data counterparts of regulation and income in (11) and control the housing, regional and macro characteristics in the following empirical model.

$$\begin{aligned} \ln p_{ijmt} &= \beta_0 + \theta(1-\tfrac{1}{2}\lambda)CALURI_j + (1-\theta)(\tfrac{3}{2}-\lambda)\phi z_{mt} \\ &\quad + \tfrac{1}{2}(1-\theta)(2\lambda-1)\phi z_{0t} + X_{ijmt}\gamma + N_{jmt}\chi + M_t\nu + \varepsilon_{ijmt} \qquad (12) \\ \text{where } z_{0t} &= \textstyle\sum_m g_{mt} z_{mt},\ \sum_m g_{mt} = 1,\ \lambda = \frac{\alpha(1-\theta)}{\alpha(1-\theta)+1} \end{aligned}$$

The log real housing price as the dependent variable has 4 subscripts that uniquely identify an observation of property transaction: property *i*, city *j*, MSA *m*, and year *t*. β_0 is the constant term. z_{mt} is the log real GDP per capita of MSA *m* where property *i* is located. z_{0t} is the log of population-weighted mean GDP per capita of California, with g_{mt} to be the population share of MSA *m* in year *t*. To take into account the structural characteristics of residential properties, we control a vector of housing characteristics X_{ijmt}.[30] In addition to per capita income, we include the number of days of good air quality in an MSA and the city mile distance to the Pacific coast as neighborhood controls in N_{jmt}. To control for the time-varying macro conditions, we use a set of macro variables M_t, including real mortgage credit growth and real 30-year fixed rate mortgage rate, with the vector of the corresponding coefficients stored in υ.[31]

Besides the coefficients of housing characteristics and macro variables, we need to estimate 3 structural parameters (θ, λ, ϕ) using 3 instruments ($CALURI_j$, z_{mt}, z_{0t}). Hence, we need the time series variation of z_{0t} to achieve identification of the model.[32] It is more convenient here to treat λ instead of α as a primitive parameter. Our estimation strategy is to use Generalized Method of Moments (GMM) to estimate the structural parameters (Hansen, 1982). GMM won't improve the estimation of the just-identified model, but the estimation method can be naturally extended to the models with additional instrumental variables to deal with endogeneity of per capita income.

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[30] The housing characteristics include the property use, the number of bedrooms, the number of bathrooms, the property age, the log property size, and the log miles to the nearest core cities. We recode the property use into three main categories: single-family residential, condominium and others. The number of bedrooms and the number bathrooms are recoded into 5 levels (0, 1, 2, 3, 4+), while the age of property is divided into 8 levels (0, 1-5, 6-10, 11-20, 21-30, 31-40, 41-50, > 50). Recoding the numbers and the age into the discrete bins allows us to control the non-linear effects on the housing price.

[31] Instead of using year dummies, we include macro controls that play a similar role.

[32] If a cross-sectional sample is used, the term z_{0t} will be absorbed in the constant term and our model will be unidentified.

5.2 Estimation Results

In Table 8, we report the estimation results. The estimation of the coefficients is based on GMM or GMM-IV estimations. In the appendix, we report the estimation of the structural parameters (θ, λ, ϕ).

5.2.1 GMM Estimators

Estimations of Model 1 and Model 2 are based on the model specification without and with the vector of housing characteristics, respectively. When housing characteristics are controlled, Model 2 shows that a standard deviation increase (or a unit increase) in the regulation (CALURI) increases the housing price by 4.2%. A 1% increase in per capita income increases the local housing price by 0.86%, while a 1% increase in the population-weighted mean per capita income of California increases the local housing price by 0.93 %. Model 1 underestimates the marginal effect of regulation by 30%, The reason is that housing characteristics are correlated with regulation. In our data, regulation is negatively correlated with the property size, the number of bedrooms and the number of bathrooms.

One caveat at interpreting the marginal effect of regulation is that the regulatory reference point is the average California city, instead of the US average. As we show in Table 3 and Figure 4, the frequency-weighted mean and median of WRLURI are 0.8 and 0.55 respectively, higher than the weighted mean and median of CALURI (0.27 and -0.01 respectively). If we extend the California estimates beyond the state, we underestimate the national regulatory impact on housing prices.[33] In the appendix, we replicate our estimations of the regulatory impact on housing price in Table 8, but instead use WALURI as the regulatory measure. We show that the estimated regulatory impact referenced to the national average is 74% larger (7.3% vs 4.2%) than the California-based regulatory impact.

5.2.2 GMM-IV Estimators

The per capita city income Z_j may be endogenous although in the model it is assumed to be exogenous. To deal with the possible endogeneity, we use the lag terms of GDP per capita and the population-weighted mean GDP per capita in California to instrument the contemporaneous variables in Model 3. In Model 4, we build on Model 3 to include three demographic variables (the share of high education, the population age, and the share of high-tech jobs) as additional instrumental variables. In Table 8, the

[33] There are two sources of underestimating the national level regulatory impact by using the estimates with CALURI and the California sample. The first source is due to the greater standard deviation of CALURI than WRLURI (1.23 vs 0.79 respectively from Table 2). All else equal, if we scale down a regulatory index (e.g. CALURI) by multiplying a factor $x < 1$, we will equivalently scale up the regulatory impact by a factor of $1/x > 1$ in estimation. The second source is related to the non-linear relationship between CALURI and WALURI. In Figure 3, WALURI roughly increases in CALURI at an increasing rate. The convex relationship indicates that specifications with WALURI will yield a higher estimate of the regulatory impact than those with CALURI.

GMM-IV estimators of the regulation and the log GDP per capita are not substantially different across Model 3 and Model 4 (0.042 and 0.84 in Model 3; 0.043 and 0.84 for Model 4).[34]

By comparing Model 2 and Model 4, we see the difference between GMM and GMM-IV estimators. Treating per capita income as exogenous in Model 2 slightly underestimates the marginal effect of regulation. In Model 4, one SD increase in the regulation increases the housing price by 4.3%, compared with 4.2% in Model 2.[35] If we use the average US regulation as the reference point, we show in the appendix that the regulatory impact on housing price is 7.6%. We report in the appendix the marginal effects of the control variables not reported in Table 8 for brevity and the structural parameter estimates through which we derive those marginal effects.

5.2.3 Factorial Contribution of Land Use Regulation to Housing Prices

Our analysis relies on CALURI as a unidimensional measure of regulation, but we can also quantify the marginal contribution of an underlying factor to the housing prices with one more step. Note that CALURI is the predicted score of the first common factor of 8 sub-indices, derived from the regression method of the principal factor analysis. We can recover the contribution of the sub-indices by regressing CALURI on the standardized sub-indices without a constant term.[36]

$$\begin{aligned} CALURI_j &= 0.418 * LPPI_j^{std} + 0.351 * LZAI_j^{std} + 0.412 * LPAI_j^{std} + 0.118 * DRI_j^{std} \\ &+ 0.255 * OSI_j^{std} + 0.151 * EI_j^{std} + 0.147 * SRI_j^{std} + 0.133 * ADI_j^{std} \end{aligned} \tag{13}$$

where the superscript *std* means that a sub-index is normalized to zero mean and unit variance. The relationship is exact without an error term, because CALURI, by definition, is a rescaled fitted value of the predicted score regression. The factor weights do not sum to one, because CALURI as the predicted score does not necessarily yield unit variance and we have normalized CALURI in the analysis.

The marginal contribution of each sub-index on the housing prices is the product of the marginal effect of CALURI reported in Table 8 and the factor weights in the predicted score regression (13).[37] In Table 9, we list percentage contribution to CALURI, which is proportional to the factor weight. Local political pressure, local project approval and local zoning approval are the leading factors contributing 21%, 21% and 18% respectively, or almost 60% in aggregate to CALURI. We show the density distribution of the 8 sub-indices in the appendix. 3 sub-indices are binary indicators (density restriction index, 6%; open space index, 13%; exactions index, 8%) and 1 sub-index is highly concentrated (supply

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[34] We also test the model specifications by including one of the three, or two of the three demographic variables as additional instrumental variables. The estimations results are quantitatively similar. The results are available upon request.

[35] Model 2 underestimates the mean per capita income of California on housing price and will overestimate the marginal impact of the log per capita income. A 1% increase in per capita income increases the local housing price by 0.84% in Model 4, compared with 0.86% in Model 2. A 1% increase in the population-weighted mean per capita income of California increases the local housing price by 1% in Model 4, compared with 0.93% in Model 2.

[36] A constant term is not needed because both CALURI and the sub-indices have been standardized to zero mean.

[37] The factor weights in (15) can be mapped to the estimated parameters of $\{\rho_s\}$ in (7).

restriction index, 7%). The approval delay index contributes 7% to CALURI. These five sub-indices contribute very little variation to CALURI.

5.3 *Estimation of Non-Linear Effects on the Log Housing Prices*

We show that regulation and income have positive impacts on the log housing price. Our estimations yield the average marginal effects. It is natural to ask whether the constant marginal effect is only local, and whether the model ignores any non-constant linear or non-linear effect consideration. Model 4 in Table 8 is treated as the benchmark model in the section where we address this question.

We introduce the non-constant marginal effects by extending the benchmark case to the full model with 1) the income-dependent marginal housing supply cost, and 2) the city-specific income elasticity of housing demand. The motivation of the first extension is that the regulatory effect may depend on the city income which reflects the land productivity. Tightening regulation in a service or industrial-oriented city will have a much stronger regulatory impact on housing prices than in an agriculture-oriented city. The first extension will introduce the interactive effect of regulation and income in the empirical model. The motivation of the second extension is that households in richer communities may pursuit quality of life and show stronger demand in response to income. The second extension will introduce the quadratic effect of income in the empirical model. We assume the extended housing supply cost and the demand shifter take the following forms respectively. The details on how we make the extensions from the benchmark cases are available in the appendix.

$$c_j = \tau_j^{\delta_1 z_j + \delta_0} c_0 \tag{14}$$

$$A_j = e^{\phi_0} Z^{\phi_2 z_j + \phi_1 - 1} \tag{15}$$

To achieve identification of the full model, we impose 3 parametric assumptions that are associated with the newly introduced parameters in (14) and (15) (available in the appendix). The idea behind those assumptions is to restrict the attention to the class of the models that nest the linear benchmark model as a special case, so those two extensions are maintained assumption and are part of the hypothesis testing.[38] The extended price equation in the full model takes the following form.

$$\begin{aligned} \ln p_{ijmt} &= \beta_0 + \theta(\delta_0 - \tfrac{1}{2}\lambda)CALURI_j + \theta\delta_1 z_{mt} \cdot CALURI_j \\ &\quad + (1-\theta)[\phi_1 - \tfrac{1}{2}(2\lambda - 1)\phi_{avg}]z_{mt} + (1-\theta)\phi_2 z_{mt}^2 + \tfrac{1}{2}(1-\theta)(2\lambda-1)\phi_{avg} z_{0t} \\ &\quad + X_{ijmt}\gamma + N_{jmt}\chi + M_t \nu + \varepsilon_{ijmt} \end{aligned} \tag{16}$$

We report the estimated regulatory effects under four specifications in Table 10 and the parameter estimates in the appendix. Model 4 is the benchmark case (δ_0 = 1 and δ_1 = 0; ϕ_0 = 0 and ϕ_2 = 0) without

[38] With either δ_0 = 1 and δ_1 = 0 or ϕ_0 = 0 and ϕ_2 = 0, we go back to the benchmark assumptions on the housing supply cost and amenity value respectively.

extension. Model 5 builds on Model 4 by including the interactive effect (ϕ_0 = 0 and ϕ_2 = 0), while Model 6 builds on Model 4 by including the quadratic effect (δ_0 = 1 and δ_1 = 0). Model 7 incorporates both effects in the benchmark case.

In Model 5, we find the interactive term is significantly positive, so the marginal effect of regulation is not constant across cities. For an average property in year 2006 located in an MSA whose log per capita income is one SD above (below) the mean, one SD increase in regulation is associated with 5.46% (3.35%) increase in housing price in Model 5, compared with a uniform 4.3% increase in Model 4. The reason why richer cities are associated with a stronger regulatory impact may be related to the complexity of the regulatory policies that are not fully incorporated in the survey.

In Model 6, we find the quadratic term of the log per capita income is significantly positive; the marginal effect of the log income has a positive and increasing impact on the log prices. For a property in year 2006 located in an MSA whose log income is one SD above (below) the MSA mean, 1% increase in the per capita income leads to 1.52% (0.72%) increase in the housing price in Model 6, compared with a uniform 1% increase in Model 4.

Model 7 shows that both the interactive and quadratic terms are significantly positive. For an average property in year 2006 located in an MSA whose log income is one SD above (below) the MSA mean, a unit increase in the regulation intensity leads to 6.88% (2.88%) increase in the housing price in Model 7, compared with a uniform 4.3% increase in Model 4. With the quadratic effect considered, the marginal effect of land use regulation is found more spatially disperse in Model 7 than in Model 5.

In Figures 6(a) and 6(b), we compare the housing price surfaces as functions of CALURI and the log income in the linear and the nonlinear models (Model 4 and Model 7) respectively.[39] The tighter the regulation is or the higher the income is, the higher the housing price. There is wide dispersion of the marginal effect of regulation by income. The increasing curvature at the corner of tight regulation and high income shows the importance of capturing the nonlinear effect.

To show the accuracy of model predictions for local price outcomes, we use data from the 6 most populated MSAs in California.[40] The central cities of these MSAs are Los Angeles, San Francisco, Riverside, San Diego, San Jose and Fresno. Figure 7 compares actual and estimated prices based on the estimates from Model 7. The estimated prices from our empirical model trace the actual prices closely.

[39] We simulate the grid points of CALURI and the log income that are normal distributed with the mean and SD estimated from the data. The grid is truncated at 1.64σ above and below each variable mean, so the grid points fall into the 90% confidence intervals along each dimension. We thus look at the space where the majority of the grid points lie.

[40] The population ranking is based on the Moody's data in 2006. We exclude Sacramento--Roseville--Arden-Arcade MSA, because the land use data from Gyourko et al (2008) is not available from the leading principal city (Sacramento). As a result, our choice of the top 6 most populated MSAs are Los Angeles-Long Beach-Anaheim MSA, San Francisco-Oakland-Hayward MSA, Riverside-San Bernardino-Ontario MSA, San Diego-Carlsbad MSA, San Jose-Sunnyvale-Santa Clara MSA, Fresno MSA.

6. Decomposing Regulatory into Partial and General Equilibrium Effects

6.1 Measuring Partial and General Equilibrium Channels

The effect of regulation on housing prices can be decomposed into two channels. The first is a partial equilibrium (PE) effect that operates through local housing supply restriction. The second channel is related to the household location choice; this is the general equilibrium (GE) effect associated with the second-order price feedback effect. Tighter regulation that makes housing more expensive will drive housing demand to neighboring cities.

We disentangle the two channels using structural estimates. By rewriting the empirical model (16) as follows, we decompose the housing price responses to the land use regulatory change.[41]

$$\ln p_{ijmt} = \underbrace{\theta(\delta_0 + \delta_1 z_{mt}) \cdot CALURI_j}_{PE\ Channel} \underbrace{- \tfrac{1}{2}\theta\lambda \cdot (CALURI_j - CALURI_k)}_{GE\ Channel} + [other\ terms]_{ijmt} \quad (17)$$

We define two channels in this way, because they achieve normalization with zero mean; with land use regulation evaluated at the mean ($CALURI_j = CALURI_k = 0$), the PE and the GE channels yield zero values.

The GE channel formalizes the spillover effect in Pollakowski and Wachter (1990) which emphasizes the spatial correlation of regulation and housing prices. The model captures the spillover effect as a consequence of household mobility. Pollakowski and Wachter (1990) and this model predict that tighter regulation in neighboring regions increases local housing prices.

6.2 Housing Price Responses through PE and GE Channels

Table 11 reports housing price responses through the PE and GE channels in response to one SD increase in regulation. We report the result by MSA, because our measure of the per capita income varies only at the MSA level.[42] Because we estimate the housing price equation using the whole California sample instead of doing estimation separately for each MSA, the GE channel is a constant according to (17). We find that a one SD increase is on average associated with 4.4% decrease in local housing prices. The GE effect is non-trivial, compared to the PE channel which amounts to 7.11% on average across MSAs. The total price response to a one SD increase in CALURI additively combines the responses of two channels and are led by those high-income MSAs including San Francisco MSA (6.59%), San Jose MSA (6.59%), Los Angeles MSA (5.27%) and San Diego MSA (4.89%).

To further explore the impact of the GE and PE effects, we apply Table 11 to simulate the impact of regulatory change in various scenarios. Our regulatory index CALURI at the city level ranges from to -3.23 to 3.38. Los Angeles City scores the highest, while Hillsborough town in San Francisco MSA

[41] Note that the GE channel is not identical to the first-order Taylor approximated term; only the marginal effect related to CALURI in the housing price equation is included in the empirical measure of the GE channel.

[42] We aggregate the city regulatory index to the MSA level using the weight provided by Gyourko et al (2008) as before.

scores the lowest. In Table 12, we conduct the counterfactual exercises of relaxing the regulation in 3 large cities (Los Angeles City, San Francisco City, San Diego City) to the MSA mean (and the MSA minimum levels). We report the housing price responses through each channel, defined as the product of the price response to one SD increase in regulation and the size of regulatory change. If Los Angeles City were to relax its regulation to the MSA mean, housing prices could be 19% lower, which equates to -35% through the PE channel and 16% through the GE channel. The housing price responses in San Francisco City and San Diego City to the regulation relaxation to their MSA means are milder, equal to -8.3% (or -13.9% + 5.6%) and -2.7% (or -5.2% + 2.5%) respectively.

Our estimates of regulatory effects are comparable to Quigley, Raphael and Rosenthal (2008) (QRR) in the San Francisco Bay Area and Jackson (2018) in California, as both construct standardized regulatory indices based on similar land use questionnaires.[43] Table 13(a) shows a comparison of QRR's results to ours. QRR's OLS estimates of the regulatory effect based on 86 cities in the Bay Area range from 1.2% to 2.2% and their estimates with regulation instrumented by political preference (*e.g.* the percent of votes in favor of Reagan in 1980) range from 3.8% to 5.3%. Our GMM-IV estimate of the regulatory effect with 25 cities in San Francisco MSA is 4.85%.[44] Table 13(b) compares Jackson's analysis of 252 California cities based on the California Land Use Survey in 2017 to ours. In the regression pooling city prices in 2000, 2006 and 2012, Jackson finds a 5% regulatory effect on housing prices. Our estimate of the average marginal effect (4.3%) in California is close to Jackson's finding of 5% regulatory effect on housing prices for a one SD increase in regulation.

Because our structural estimates are not time-varying, the estimated regulatory effects on housing prices will not be indexed by time. There is concern that the cross-sectional Wharton survey may misrepresent the regulation in the years distant from the survey year (2006). Hence, it is important to see how the regulatory effect may vary if it is estimated by year. We run a set of annual price regressions and plot the marginal effects of CALURI by year in Figure 8. The marginal effect of regulation is increasing over time, with a 4% estimated effect for the survey year close to the structurally estimated regulatory effect (4.3%). The increasing trend may reflect the ever-increasing marginal effect of regulation. Alternatively, it could be simply a result of changing distribution of regulation over time. Without additional data to inform us of the regulation dynamics, we cannot tell which force is dominant.

[43] The local survey conducted by QRR is based on the questionnaires of Qyourko, Saiz and Summers (2008) but is adapted to California jurisdictions.

[44] We compare the QRR's estimates to ours under the specification without neighboring controls (i.e. the number of days with good air quality and the mile distance to the Pacific coast). If we include the neighboring controls, we get a higher but still comparable estimate of the regulatory effect (6.58%).

7. The Spillover Effect of Land Use Regulation on Housing Prices

Pollakowski and Wachter (1990) using data for a single county (Montgomery, Maryland) find that the relative restrictiveness of regulation between neighboring and home cities has a positive spillover effect on housing prices in the home city. Since then, regulatory spillover across housing market is less attended in both theory and empirical work. We formalize the spillover effect in a model with household mobility. Our dataset is much larger and representative. We use residential transaction data in California to confirm the existence and the positive impact of the intra-metro spillover effects. We find that the home regulatory impact on home housing prices is stronger, once the relative restrictiveness of regulation is controlled. Consistent with Pollakowski and Wachter (1990), we show the previous finding holds in more recent data and more widely in the metro areas. Nonetheless the results above are for a GE effect which is constant throughout California. We would like to measure such effects with more spatial details but lack the data to do so for all of California. In the following we do model a spatially varying GE effect in MSAs for which we have sufficient data.

7.1 Measuring the Spillover Effect by MSA

To capture the relative restrictiveness of regulation for a city, we define the relative restrictiveness index (RRI) as the difference between neighboring and home regulatory indices whose marginal effect measures the spillover effect.

$$RRI_j = CALURI_{-j} - CALURI_j \qquad (18)$$

An ideal case of defining neighboring regulatory index would be to use the regulatory information on the neighboring cities. Because the regulation survey is subject to lower response rates in certain metro areas, we previously assume an outside moving option which is a city with average income and regulation and is identical to all cities. The assumption mitigates the survey bias by relying less on the spatial information in estimation. We relax the assumption and work on a measure of city-specific moving options. We assume the form of the neighboring regulatory index of city j as the weighted average of the regulatory indices in California and consider two alternative spatial weighting measures of the neighboring indices based on the city proximities.

$$CALURI_{-j} = \sum_{k \neq j} weight_{jk} \cdot CALURI_k \qquad (19)$$

$$\begin{aligned} &\text{inv. sq. distance: } weight_{jk} = x_{invdist2} / d_{jk}^2 \\ &\text{gravity: } weight_{jk} = x_{gravity} z_j z_k / d_{jk}^2 \end{aligned} \qquad (20)$$

where $x_{invdist2}$, and $x_{gravity}$ are constants to make sure that the sum of the weights is equal to 1. The first measure called the inverse distance square puts more weight on the regulatory indices of nearby cities than remote cities. The second case generalizes the first one by taking a gravitational form. The gravity model puts weight on the per capita income of the home and neighboring cities, adjusted by the distance.

Note that (19) nests the case of identical outside moving option as a special case in the previous estimations (RRI_j = -$CALURI_j$). If equal weight is assigned to all cities in California regardless of the distance, the neighboring index $CALURI_{-j}$ will be the mean CALURI, which is zero by construction. Although the special case may mitigate the survey bias due to low response rate and reduce the reliance on spatial information, it provides a robust but coarse measure of relative restrictiveness of regulation.

7.2 Additional Data

We collect additional data, because previous analysis relying on MSA per capita income cannot identify the intra-metro spillover effect and we will now examine MSAs separately. Our estimations in previous sections exclude the discussion of the MSA specific spillover effect due to limited data availability.[45] There is no series of per capita income that covers the whole sample period from 1993 to 2017 at the city level. An additional data issue is the low response rate of the Wharton Land Use Survey in some MSAs.[46] The construction of RRI which relies on spatial information may be severely biased towards the cities responding to the Wharton survey.

To overcome the data issue, we additionally collect census tract data from the tract-block Summary File of the 2014 American Community Survey (ACS) 5-year estimates. The 5-year survey spans from 2010 to 2014 but the estimates do not represent any single year in the range.[47] We calculate the city-level per capita income by averaging the tract-level median income per capita and using the tract population as the weight.

To match the time frame of the income data, this analysis uses transactions in California in 2014. We thus exclude the variables that don't exhibit cross-sectional variations in an MSA to prevent a collinearity problem.[48] The independent variables include the city regulation index, the log per capita income (linear, quadratic) and housing characteristics in the benchmark estimation (Model 4 in Table 8). We select four MSAs that appear to suffer a low response bias in the Wharton survey and do not have too few within the metro area; these are: (Los Angeles-Long Beach-Anaheim MSA, San Francisco-

[45] We decide to use more data to produce more precise estimates and to exclude the spillover effect in the previous estimations based on MSA per capita income.

[46] In the appendix, we report the response rate of cities by CBSA (MSA and μMSA) in the Wharton Land Use Survey.

[47] The first wave of the tract level data is 2009 ACS 5-year estimates, but we use the wave of 2014 ACS 5-year estimates to exclude any unobservable consequence of the Great Recession on the housing market. 2014 ACS 5-year estimates is the wave that is closest to the time of the Wharton Land Use Survey with no single year falling into the Great Recession.

[48] The excluded independent variables in the section are the growth rate of the household mortgage debt, the real 30-year fixed-rate mortgage rate, and the log of population-weighted mean GDP per capita of California, the number of days with good air quality.

Oakland-Hayward MSA, San Diego-Carlsbad MSA, Oxnard-Thousand Oaks-Ventura MSA, with LA, SF, SD and VT respectively for short notations).[49]

In Figure 9, we show the distribution of the CALURI and RRI in these cities. RRI under different weight measures in (20) show similar distributional patterns, with unimodal shapes and fat tails. In Figure 10, we show the scatter diagrams of CALURI and RRI by city. There is a strong negative correlation between CALURI and RRI under the two spatial weighting measures (-0.92 and -0.93 respectively). We separately mark the cities in the four selected MSAs (LA, SF, SD, VT) and show that the negative correlation still holds within each metro area.

7.3 Estimating the Spillover Effect

In Table 14, we report the estimated home regulatory effects (or PE effects) and the spillover effects (or GE effects) for the four selected MSAs (LA, SF, SD, VT). We report three model specifications for each MSA. Similar to the method adopted by Pollakowski and Wachter (1990), we use OLS in the estimations.[50] Column 1 in Table 14 reports regression estimates with the home regulatory impact (CALURI) but without the relative restrictiveness (RRI). Column 2 separates the PE effect from the total effect by deducting the constant GE effect in Table 11. Columns 3 and 4 report regression estimates by including both CALURI and RRI under the two weighting measures. The cross-sectional estimations capture 43%-61% of the log price variations, depending on the specifications and MSAs.

We show that the home regulatory effect (CALURI) and the spillover effect (RRI) are significantly positive for all four selected MSAs. Without controlling RRI, the home regulatory effect will be underestimated. Using Los Angeles MSA as an example, the home regulatory effect estimate without RRI is 5.95%, compared to 14.7% in Column 3 and 18.2% in Column 4 with RRI controlled. Model 1 without RRI controlled would produce a reasonable estimate of the home regulatory effect under one of following two assumptions: 1) if RRI were uncorrelated with CALURI, or 2) if the spillover effect is economically small. However, we show in Figure 9 that RRI is not randomly distributed but negatively correlated with CALURI, rejecting the uncorrelated assumption. The estimated regulatory spillover effects for selected MSAs are far from zero, as is shown by the significant coefficients of RRI in Table 14.

[49] To choose MSAs, we set the following criteria: (1) there are at least 10 cities in an MSA covered by the Wharton Land Use Survey; (2) an MSA has more than 1 principal city based on the definition in the historical delineation files of metropolitan and micropolitan statistical areas (2006) from the Census Bureau; (3) more than 50% of the leading principal cities (listed in the name of an MSA) are covered by the Survey. Three MSAs survive the criteria: Los Angeles-Long Beach-Anaheim MSA, San Francisco-Oakland-Hayward MSA, and San Diego-Carlsbad MSA (For San Francisco MSA, it is long known as San Francisco–Oakland–Fremont MSA until 2013). We additionally add Oxnard-Thousand Oaks-Ventura MSA as another case due to the high response rate (70%) among its 10 cities.

[50] Instrumenting the per capita income with city-level demographic variables (using the mean population age and share of high education aggregated from the tract level) won't qualitatively change the estimated regulatory and spillover effect of the selected MSAs.

The estimates of Model 1 in Table 14 are interpreted as a mixture of the regulatory effect through the PE and GE channels. The estimates in Column 1 are not directly comparable across MSAs, because the GE effect will depend on the intra-metro distributions of regulation whose spatial patterns are not identical across metro areas (Figure 2). Our previous estimations in Tables 8 and 10 based on all California sample proceed with the uncorrelated assumption, but we separate the PE channel from the GE channel using the structural model to yield comparable estimates of home regulatory effects. An adjustment to the estimated regulatory effect in Column 1 by a constant GE effect produces a 10.4% home regulatory effect in Los Angeles MSA in Column 2. If we can construct a reliable spatial measure of relative restrictiveness of regulation as Columns 3 and 4, controlling relative restrictiveness provides a simple way to correctly estimate the spillover effect (RRI) and the regulatory effect through the PE channel.[51]

As the Los Angeles MSA is geographically close to the Oxnard MSA, it is natural to ask whether the spillover effect in the Oxnard MSA is across metro and is related to Los Angeles MSA. We pool the sample in those two MSAs and reproduce the previous analysis. We find that regression models based on the MSA-combined sample yield larger coefficients on CALURI and RRI than the models based on the separate MSA sample. If the spillover effects were intra-metro only, we should expect the combined sample to reproduce the average coefficients on CALURI and RRI from the separate MSA samples. Our finding suggests that the regulatory spillover not only exists within a metro area but also across two neighboring MSAs.

In Table 15, we ask whether the home regulatory effect and the spillover effect are similar for less and more regulated cities. We focus on the Los Angeles MSA because it is one of the MSAs with the largest number of cities covered in the Wharton survey. We divide 48 cities into high and low regulation groups by the median regulation in the Los Angeles MSA. We conduct similar regression analysis with and without RRI. We find that tighter regulation in the high regulation group increases housing prices more, as shown by the higher coefficient of CALURI in more regulated cities. We also find that cities with a relatively low regulatory index are more impacted by regulation elsewhere.

8. Conclusion

In this paper, we develop a general equilibrium framework to determine the spillover effects of land use regulation on housing prices in cities in California over the years 1993 to 2017. We use house transaction prices and characteristics along with data on macro credit supply and regional per capita income together

[51] The spillover effect provides an interpretation why we see negative regulatory estimates on the regulation index. The question is whether it provides mixed evidence on the regulatory effect on housing price. For example, in the Oxnard MSA, Column 1 produces a negative coefficient on CALURI, while Columns 3 and 4 shows that RRI has a larger coefficient than CALURI, indicating stronger regulatory spillover than the home regulatory effect.

with the Wharton Residential Land Use Survey (Gyourko, Saiz and Summers, 2008) to identify the impacts of land use regulation on housing prices.

We identify the separate channels through which land use regulation can impact housing prices. Specifically, we characterize a partial equilibrium channel through which home locality land use regulation increases the cost of local housing production. In addition, we show a general equilibrium spillover effect in which demand shifts to other localities. The measured effect of empirical studies that show the impact of local regulation on local housing prices combines these two effects. The direct effect of regulation on housing prices is underestimated in the absence of allowing for a general equilibrium effect that captures the extent to which local regulation increases the demand for housing elsewhere. That is, the OLS estimated effects in the literature cannot be used to estimate the impact of land use regulation on housing prices, if regulation in surrounding areas changes.

For MSAs for which we have a sufficient coverage of regulation throughout the region we can define and measure a relative regulatory restrictiveness index as the difference between the neighboring and home regulatory indices and report findings on the direct and spillover effects on housing prices.

Our estimated effects for Los Angeles, the city whose housing prices are most impacted by land use regulation in our study, show that if land use regulation in LA were to be decreased to the level observed in the least regulated city in the region, housing prices would decline by approximately 28%. However, in the absence of a spillover effect, the price decline would be twice as high. The existence of housing markets surrounding LA with less stringent regulation lessens the impact of LA's land use regulation on its housing prices If regulation increases in these surrounding localities, the impact of regulation in LA would increase even without any increase in regulation within LA itself.

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Tables

Table 1. Summary of Recent Studies on Land Use Regulation and Housing Prices

Paper (Year)	Market	Method	Regulatory Measure	Housing Price Measure	Housing data Period	Regulatory Effect on Prices
Quigley and Raphael (2005)	407 California cities	OLS	Number of growth control measures (out of a total of 15) adopted by each city	Housing price index constructed from Census Public Use Micro data Sample (constant-quality index)	1990, 2000	1 additional measure leads to 3.1% increase in prices in 1990 and 4.5% in 2000
Ihlanfeldt (2007)	105 cities in Florida	OLS, 2SLS	Number of restrictive land use management techniques (out of a total of 13) currently used by each city	Sales data from property tax rolls (with property size and age)	2000-2002	1 more regulation leads to 3% increase in price
Quigley, Raphael and Rosenthal (2008)	86 cities in San Francisco Bay Area	OLS, IV	Simple sum/principal factor of standardized 10 sub-indices from Berkeley Land Use Survey	Housing prices with characteristics from 2000 Census	2000	1 SD increase leads to 1.1%-2.2% with OLS, or 3.8%-5.3% with IV estimation
Glaeser and Ward (2009)	187 cities in Great Boston	OLS	A simple sum of three dummies as the regulatory barriers index (1 if a town has passed a rule that goes beyond the state standards regarding septic systems, wetlands and sub-divisions).	Banker and Tradesman data on housing price transactions with housing characteristics	2000-2005	1 additional regulation leads to a 10% increase in price.
Huang and Tang (2012)	326 cities in US	OLS	WRLURI	Zillow hedonic price index	2000-2009	1 SD increase leads to 5% price increase between 2000 to 2006; or 4% price decrease between 2006 and 2009
Kok, Monkkonen, Quigley (2014)	110 cities in San Francisco Bay Area	OLS	First measure is the number of independent reviews and approvals required by a locality before issuance of a building permit; second measure is the number of separate reviews by local authorities required to approve a zoning change.	average selling price by quarter year, from Dataquick	1990-2000	1 SD decrease (three public reviews) in the number of reviews required for approval of a building permit (zone change) related to a decrease in house prices of 4–8% (1-2%)
Jackson (2018)	252 cities in California	OLS	Standardized sum of the 9 sub-indices from California Land Use Survey in 2018	Zillow hedonic price index	Jan 2000, April 2006, Jan 2012	1 SD increase leads to 5% increase in price (pooled regression)

Table 2. Sample Coverage by Geographical Cities

	City	County	CBSA	Count
Land Use Sample	179	39	25	5,318,379
Unmatched Sample	963	47	25	7,403,052

Table 3. Summary Statistics of Land Use Regulation Indices

	Mean	Median	SD	Pct.25	Pct.75
LPPI	0.47	0.11	1.08	-0.31	1.09
LZAI	1.87	2	0.61	1	2
LPAI	1.69	1	0.98	1	2
DRI	0.15	0	0.35	0	0
OSI	0.87	1	0.33	1	1
EI	0.93	1	0.26	1	1
SRI	0.19	0	0.77	0	0
ADI	9.04	8.06	4.51	5.67	12.13
CALURI	0.27	-0.01	1.23	-0.41	0.6
WRLURI	0.8	0.55	0.79	0.16	1.5

Note: local political pressure index (LPPI), local zoning approval index (LZAI), local project approval index (LPAI), density restriction index (DRI), open space index (OSI), exactions index (EI), supply restriction index (SRI), approval delay index (ADI). California Land Use Regulation Index (CALURI), Wharton Residential Land Use Regulation Index (WRLURI). Frequency weights of the property transactions are used. Source: Gyourko, Saiz and Summer (2008) and authors' calculation.

Table 4. Distribution of Residential Property Use

	Land Use Sample		Unmatched Sample	
Property Type	Frequency	Percent	Frequency	Percent
Single Family Residential	4,045,001	31.80	6,200,178	48.74
Townhouse	13,401	0.11	31,418	0.25
Cluster Home	39,918	0.31	45,049	0.35
Condominium	1,133,241	8.91	951,460	7.48
Cooperative	859	0.01	323	0.00
Row House	336	0.00	702	0.01
Planned Unit Development	84,951	0.67	159,699	1.26
Inferred Single Family Residential	672	0.01	14,223	0.11
Total	5,318,379	100.00	7,403,052	100.00

Note: the total sample is the non-foreclosed residential sales transactions in California from 1993 to 2017. Source: ZTRAX and authors' calculation.

Table 5. Summary Statistics of Property Characteristics

	Mean	Median	SD	Pct.25	Pct.75
Land Use Sample					
Sales Price	369,615	282,102	620,425	169,943	453,920
Sq.Ft.	1,699.40	1,503.00	858.78	1,162.00	2,011.00
Price/Sq.Ft	221.27	181.26	518.6	115.82	283.93
Age of Property	30	26	24.56	9	46
No.of Bathroom	2	2	0.81	2	2
No.of Bedrooms	3.03	3	1.04	2	4
Miles to Core Cities	28.08	8.14	240.19	4.44	14.5
Unmatched Sample					
Sales Price	352,330	270,609	643,300	165,749	427,337
Sq.Ft.	1,778.34	1,574.00	1,048.22	1,217.00	2,128.00
Price/Sq.Ft	199.64	164.88	761.11	108.91	250.08
Age of Property	27.8	24	23.13	8	44
No.of Bathroom	2.05	2	0.8	2	2
No.of Bedrooms	3.16	3	0.95	3	4
Miles to Core Cities	52.34	10.99	362.95	5.83	20.65

Note: Sales Price and Price/Sq.Ft are inflation adjusted to Jan. 2006 US dollars, using the Consumer Price Index for All Urban Consumers: Housing (FRED: CPIHOSNS). Source: ZTRAX and authors' calculation. ZTRAX database is provided by Zillow Group.

Table 6. Summary Statistics of Instrumental Variables

	Mean	Median	SD	Pct.25	Pct.75
share of high education (%)	35.92	35.2	8.02	29.12	42.10
population age	34.48	34.3	2.22	32.72	36.27
share of high-tech jobs (%)	6.84	5.37	5.90	2.94	8.11

Note: variables are weighted by the MSA population. Statistics are calculated based on the pooled time-series cross-sectional sample at the MSA level. Source: American Community Survey, Moody's Analytics.

Table 7. Correlation Matrix: Instrumental Variables

	GDP pc	L.GDP pc	high educ %	high-tech %	pop. age
GDP pc	1.000				
L.GDP pc	0.992	1.000			
high educ %	0823	0.820	1.000		
high-tech %	0.651	0.627	0.706	1.000	
pop. age	0.753	0.762	0.905	0.405	1.000

Note: all variables are in log form. Correlation is weighted by the MSA population. Source: American Community Survey, Moody's Analytics.

Table 8a. Benchmark Estimation: Marginal Effect of Regulation and Income on Log Housing Prices (with Distance to Coast and air quality measure)

	Model 1 GMM	Model 2 GMM	Model 3 GMM-IV	Model 4 GMM-IV
CALURI	0.0293***	0.0420***	0.0419***	0.0432***
	(0.000)	(0.000)	(0.000)	(0.000)
log GDP per	0.756***	0.855***	0.838***	0.840***
capita	(0.002)	(0.001)	(0.001)	(0.001)
log Avg.	1.065***	0.933***	0.979***	0.999***
GDP per cap	(0.005)	(0.004)	(0.004)	(0.004)
Observations	5,259,215	5,259,215	5,259,215	5,259,215

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Omitted control variables in Models 2-4: the number of bedrooms, the number of bathrooms, log mile distance to the nearest core city, the property age, the property type (single family/condo), the property size, the mortgage growth rate, the 30-year FRM rate, log mile distance to the Pacific coast, the number of good days (air quality). The lag terms of log real GDP per capita and log mean GDP per capita in California are used as IVs of their contemporaneous terms in Models 3-4; the share of high education, the population age and the share of high-jobs are additional IVs of Model 4. Models are estimated using GMM. The marginal effects of the omitted control variables are available in the appendix.

Table 8b. Alternative Estimation: Marginal Effect of Regulation and Income on Log Housing Prices (without Distance to Coast and air quality measure)

	Model 1' GMM	Model 2' GMM	Model 3' GMM-IV	Model 4' GMM-IV
CALURI	0.0195***	0.0293***	0.0290***	0.0297***
	(0.000)	(0.000)	(0.000)	(0.000)
log GDP per	1.231***	1.326***	1.311***	1.291***
capita	(0.001)	(0.001)	(0.001)	(0.001)
log Avg.	0.496***	0.352***	0.369***	0.432***
GDP per cap	(0.005)	(0.004)	(0.004)	(0.004)
Observations	5,259,215	5,259,215	5,259,215	5,259,215

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Omitted control variables in Models 2-4: the number of bedrooms, the number of bathrooms, log mile distance to the nearest core city, the property age, the property type (single family/condo), the property size, the mortgage growth rate, the 30-year FRM rate. The lag terms of log real GDP per capita and log mean GDP per capita in California are used as IVs of their contemporaneous terms in Models 3-4; the share of high education, the population age and the share of high-jobs are additional IVs of Model 4. Models are estimated using GMM.

Table 9. Contribution of Sub-indices to CALURI

Sub-index	Sub-index Name	Contribution to CALURI (%)
LPPI	local political pressure index	21.06
LZAI	local zoning approval index	17.68
LPAI	local project approval index	20.76
DRI	density restriction index	5.94
OSI	open space index	12.85
EI	exactions index	7.61
SRI	supply restriction index	7.41
ADI	approval delay index	6.70
Total		100.00

Note: The share of contribution to CALURI is derived from the predicted score regression in the principal factor analysis.

Table 10. Estimation with Non-Linear Effects: Marginal Effect on Log Housing Prices

	Model 4 GMM-IV	Model 5 GMM-IV	Model 6 GMM-IV	Model 7 GMM-IV
CALURI	0.0432*** (0.000)	-0.162*** (0.004)	0.0460*** (0.000)	-0.341*** (0.004)
log GDP per capita	0.840*** (0.001)	0.833*** (0.001)	-6.756*** (0.030)	-7.172*** (0.030)
Avg.log GDP per capita	0.999*** (0.004)	0.994*** (0.004)	0.934*** (0.004)	0.924*** (0.004)
CALURI*log GDP per capita		0.0518*** (0.001)		0.0980*** (0.001)
log GDP per Capita squared			0.990*** (0.004)	1.042*** (0.004)
Observations	5,259,215	5,259,215	5,259,215	5,259,215

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Omitted control variables in Models 4-7: the number of bedrooms, the number of bathrooms, log mile distance to the nearest core city, the property age, the property type (single family/condo), the property size, the mortgage growth rate, the 30-year FRM rate, log mile distance to the Pacific coast, the number of good days (air quality). The lag terms of the log real GDP per capita and log mean GDP per capita in California are used as IVs of their contemporaneous terms; the share of high education, the population age and the share of high-jobs are additional IVs of Models 4-7. Models are estimated using GMM.

Table 11. Housing Price Responses (%) to +SD CALURI by MSA

MSA	PE	GE	total
Bakersfield	7.11	-4.44	2.67
Chico	7.12	-4.44	2.68
Fresno	6.99	-4.44	2.55
Hanford-Corcoran	3.00	-4.44	-1.44
Los Angeles-Long Beach-Anaheim	9.71	-4.44	5.27
Madera	5.06	-4.44	0.62
Merced	3.40	-4.44	-1.04
Modesto	5.56	-4.44	1.11
Napa	9.08	-4.44	4.64
Oxnard-Thousand Oaks-Ventura	7.31	-4.44	2.87
Redding	8.37	-4.44	3.93
Riverside-San Bernardino-Ontario	5.11	-4.44	0.67
Sacramento-Roseville-Arden-Arcade	9.27	-4.44	4.82
Salinas	6.82	-4.44	2.38
San Diego-Carlsbad	9.33	-4.44	4.89
San Francisco-Oakland-Hayward	11.03	-4.44	6.59
San Jose-Sunnyvale-Santa Clara	11.03	-4.44	6.59
San Luis Obispo-Paso Robles-Arroyo Grande	8.46	-4.44	4.02
Santa Cruz-Watsonville	7.57	-4.44	3.12
Santa Maria-Santa Barbara	8.79	-4.44	4.35
Santa Rosa	8.00	-4.44	3.56
Stockton-Lodi	5.59	-4.44	1.15
Vallejo-Fairfield	5.72	-4.44	1.28
Visalia-Porterville	3.99	-4.44	-0.45
Yuba City	4.40	-4.44	-0.04
mean	7.11	-4.44	2.67

Note: the numbers reported by MSA are price responses of two channels to +one SD change of CALURI, using the estimates from Model 7. PE = partial equilibrium. GE = general equilibrium.

Table 12. Counterfactual Price Changes (%) in Response to Loosening Regulation

City CALURI	Los Angeles City (3.38)		San Francisco City (1.04)		San Diego City (0.30)	
Scenario	MSA Mean (-0.20)	MSA Low (-1.89)	MSA Mean (-0.22)	MSA Low (-3.23)	MSA Mean (-0.25)	MSA Low (-1.04)
PE (%)	-34.73	-51.18	-13.89	-47.12	-5.19	-12.48
GE (%)	15.88	23.40	5.59	18.97	2.47	5.94
Total (%)	-18.85	-27.78	-8.30	-28.15	-2.72	-6.54

Note: To calculate the price changes in response to loosening regulation, we multiply the marginal effect of regulation through each channel (available from Table 11) by the difference of the CALURI of a selected scenario and the CALURI of a selected city. PE = partial equilibrium. GE = general equilibrium.

Table 13a. Comparison to Quigley, Raphael and Rosenthal (2008)

Quigley, Raphael and Rosenthal (2008)			
Housing Market examined	86 cities in San Francisco Bay Area		
Source of Price data	Home value from 2000 US Census		
Housing characteristics	No. of bedrooms/rooms, property type/age, quality of kitchen/bath		
Regulatory Index	BLURI (from Berkeley Land Use Survey, 2008), 10 sub-indices		
Estimation method	OLS and IV		
Results	Total (OLS)		Total (IV)
Marginal effect of regulation on prices	1.2%-2.2%		3.8%-5.3%
This paper			
Corresponding market	25 cities in San Francisco-Oakland-Hayward, MSA		
Source of Price data	ZTRAX, 1993-2017		
Housing characteristics	No. of bed/bathrooms, property type/size/age, miles to core city		
Regulatory Index	CALURI (from Wharton Land Use Survey, 2008), 8 sub-indices		
Estimation method	GMM-IV		
Results (w/ regional var.)	PE Channel	GE Channel	Total
Marginal effect of regulation on prices	10.64%	-4.44%	6.58%
Results (w/o regional var.)	PE Channel	GE Channel	Total
Marginal effect of regulation on prices	6.66%	-1.81%	4.85%

Note: The average marginal effect of regulation in the Bay Area in Quigley et al (2008) and in our paper comes from their Table 9.9 and our Table 11 respectively. Regional variables include miles to the Pacific coast and the number of good days (air quality).

Table 13b. Comparison to Jackson (2018)

Jackson (2018)			
Housing market examined	252 cities in California		
Source of Price data	Zillow hedonic price index (2000,2006, 2012)		
Housing characteristics	NA		
Regulatory Index	CaLURI (from California Land Use Survey, 2018), 9 sub-indices		
Estimation method	OLS		
Marginal effect of regulation on prices	5%		
This paper			
Corresponding market	185 cities in California		
Source of Price data	Residential transaction from ZTRAX, 1993-2017		
Housing characteristics	No. of bed/bathrooms, property type/size/age, miles to core city		
Regulatory Index	CALURI (from Wharton Land Use Survey, 2008), 8 sub-indices		
Estimation method	GMM-IV		
Results (w/ regional var.)	PE channel	GE Channel	Total
Marginal effect of regulation on prices	8.76%	-4.44%	4.32%
Results (w/o regional var.)	PE channel	GE Channel	Total
Marginal effect of regulation on prices	4.78%	-1.81%	2.97%

Note: The average marginal effect of regulation in California in Jackson (2018) and in this paper comes from their Table 3 and our Table 9 respectively. Our total effect and GE effect come from Table 8 and Table 11 respectively. Regional variables include miles to the Pacific coast and the number of good days (air quality).

Table 14. Regressions with and without Spillover Effect in Selected MSAs

MSA		Without RRI		With RRI	
	Variable	Unadjusted	Adjusted	Inv.dist2	Gravity
Los Angeles-Long Beach-Anaheim	CALURI	0.0595***	0.1039	0.147***	0.182***
		(0.0015)		(0.0093)	(0.0100)
	RRI		0.0444	0.0878***	0.124***
				(0.0091)	(0.0099)
	Adjusted R^2	0.563		0.564	0.565
	N	52,102		52,102	52,102
	Variable	Unadjusted	Adjusted	Inv.dist2	Gravity
San Francisco-Oakland-Hayward	CALURI	0.0158*	0.0602	0.0600***	0.0715***
		(0.0081)		(0.017)	(0.016)
	RRI		0.0444	0.0410***	0.0512***
				(0.014)	(0.013)
	Adjusted R^2	0.510		0.511	0.511
	N	19,137		19,137	19,137
	Variable	Unadjusted	Adjusted	Inv.dist2	Gravity
San Diego-Carlsbad	CALURI	0.125***	0.1694	0.257***	0.262***
		(0.0076)		(0.023)	(0.021)
	RRI		0.0444	0.103***	0.106***
				(0.018)	(0.016)
	Adjusted R^2	0.604		0.605	0.605
	N	21,985		21,985	21,985
	Variable	Unadjusted	Adjusted	Inv.dist2	Gravity
Oxnard-Thousand Oaks-Ventura	CALURI	-0.0191*	0.0253	0.0607***	0.0679***
		(0.0089)		(0.022)	(0.022)
	RRI		0.0444	0.0805***	0.0879***
				(0.018)	(0.019)
	Adjusted R^2	0.429		0.431	0.431
	N	6,272		6,272	6,272
	Variable	Unadjusted	Adjusted	Inv.dist2	Gravity
Los Angeles MSA and Oxnard MSA Combined	CALURI	0.0624***	0.1064	0.163***	0.205***
		(0.0015)		(0.0080)	(0.0087)
	RRI		0.0444	0.101***	0.145***
				(0.0079)	(0.0086)
	Adjusted R^2	0.545		0.546	0.547
		58,374		58,374	58,374

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. The dependent variable is the log housing prices. The regressions are run separately for each selected MSAs. CALURI = California Land Use Regulation Index; RRI = Relative Restrictiveness Index defined as the difference between neighboring and home CALURI. The column *Unadjusted* reports the regression without RRI controlled. The column *adjusted* report the regulatory effect net of the GE effect (listed in the row of RRI) from Table 11. The column *Inv.dist2* (*Gravity*) reports the regression with the inverse distance square (the city income per capita divided by the squared distance) as the weight on neighboring CALURI. Omitted control variables in regression models include log city-level per capita income where a property is located and its squared term, the number of bedrooms, the number of bathrooms, log mile distance to the nearest core city, the property age, the property type (single family/condo), the property size. We use the housing transactions in 2014 from ZTRAX. The data of the city-level per capita income is aggregated from the census tract data from the Summary File of the 5-year ACS 2010-2014.

Table 15. Regressions with and without Spillover Effect by High and Low Regulated Cities in Los Angeles-Long Beach-Anaheim MSA

	No RRI		With RRI (Invdist2)		With RRI (gravity)	
	Low	High	Low	High	Low	High
CALURI	-0.208***	0.0461***	0.0771**	0.183***	0.0901**	0.195***
	(0.0097)	(0.0022)	(0.039)	(0.010)	(0.037)	(0.011)
RRI			0.212***	0.144***	0.222***	0.155***
			(0.027)	(0.011)	(0.026)	(0.012)
Adjusted R^2	0.734	0.555	0.735	0.558	0.735	0.558
Observations	16,528	35,574	16,528	35,574	16,528	35,574

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. The dependent variable is the log housing prices. 48 cities in the Los Angeles-Long Beach-Anaheim MSA are divided into high and low regulation group. The regressions are run separately for cities with high and low city regulation. CALURI = California Land Use Regulation Index; RRI = Relative Restrictiveness Index defined as the difference between neighboring and home CALURI. *Benchmark* is the case where RRI is not controlled. *Inv.dist2* uses the inverse distance square to weigh neighboring CALURI. *Gravity* indicates the specification with the city-level income per capita divided by the squared distance as the weight. Omitted control variables in all specifications include log city-level per capita income where a property is located and its squared term, the number of bedrooms, the number of bathrooms, log mile distance to the nearest core city, the property age, the property type (single family/condo), the property size. We use the housing transactions in 2014 from ZTRAX. The data of the city-level per capita income is aggregated from the census tract data from the Summary File of the 5-year American Community Survey 2010-2014.

Figures

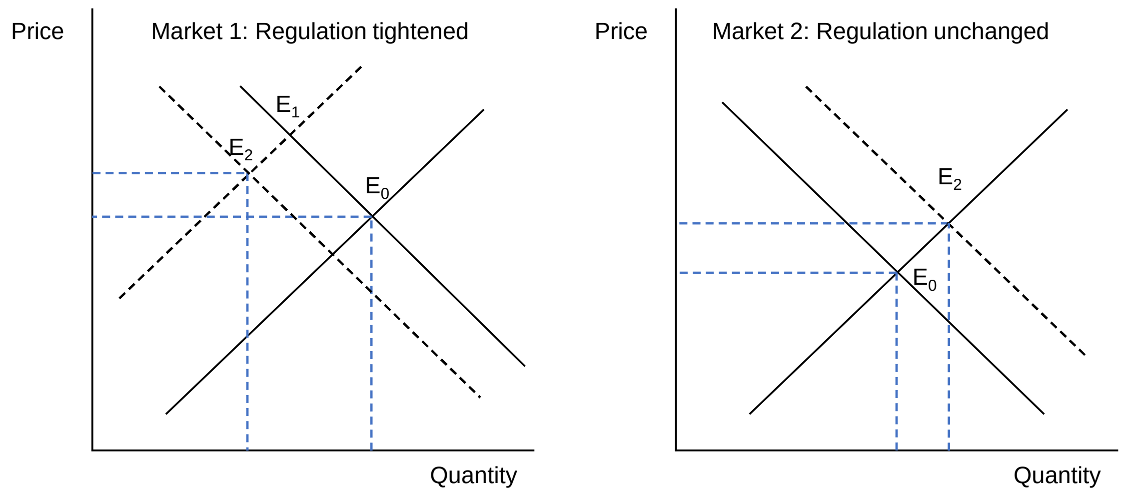


Figure 1: graphical illustration of regulatory impact on housing prices. The example considers 2 housing markets where regulation in Market 1 is tightened and regulation in Market 2 remains unchanged. E_0 is the initial equilibrium. The change from E_0 to E_1 shows the regulatory effect through the partial equilibrium channel. The change from E_1 to E_2 shows the general equilibrium effect that reallocates housing demand between two markets.

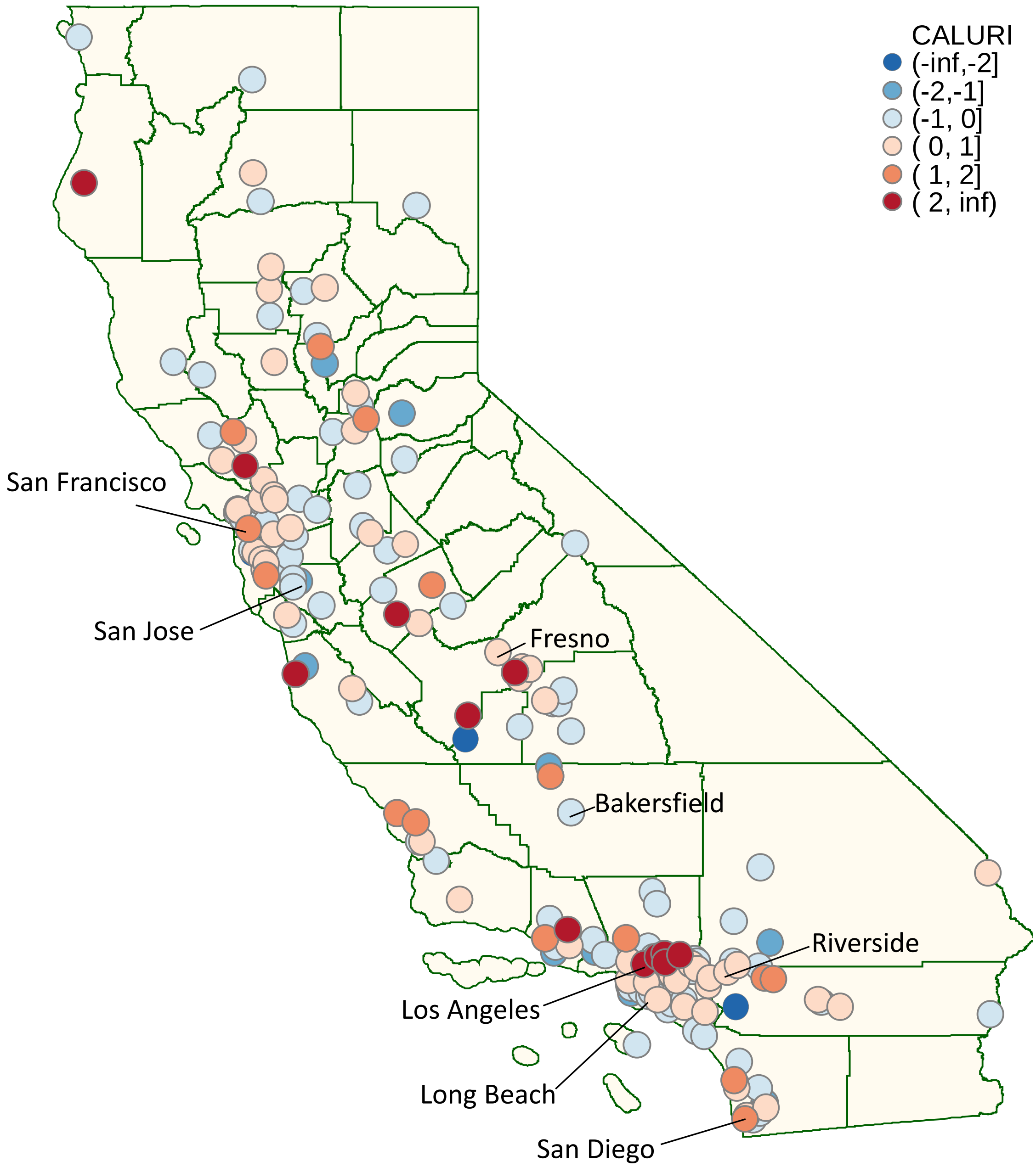


Figure 2: spatial distribution of land use regulation intensity in California. California Land Use Regulation Index (CALURI) is based on the sub-indices from WRLURI. A higher index value indicates higher regulation intensity. There are 185 jurisdictions in total.
Source: Gyourko, Saiz and Summers (2008) and authors' calculation.

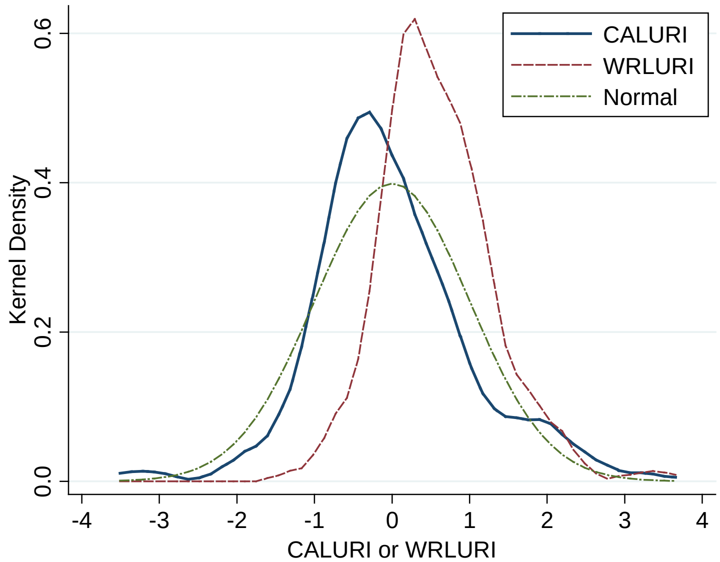
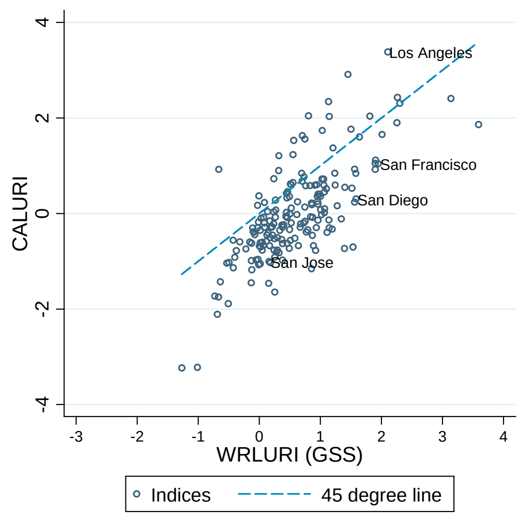
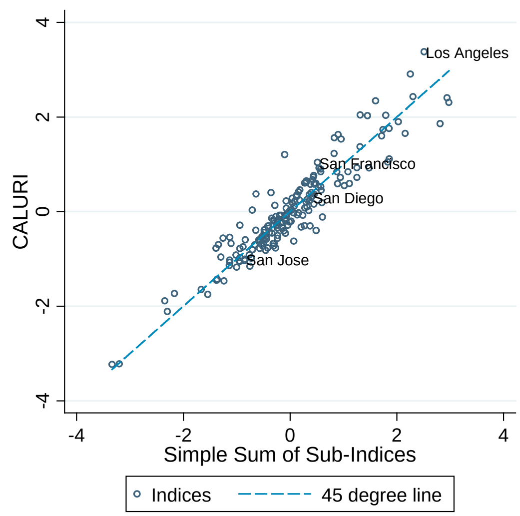


Figure 3: comparison of the kernel density of California Land Use Regulation Index (CALURI), Wharton Index (WRLURI) with California cities and the normal density. CALURI is based on the 8 sub-indices in WRLURI that exhibit intra-state variation. A higher index value indicates higher regulation. Source: Gyourko, Saiz and Summers (2008) and authors' calculation.



(a) CALURI vs WRLURI



(b) CALURI vs Simple Sum of Sub-indices

Figure 4: quantile-quantile plots of WRLURI, CALURI and Simple Sum of Sub-indices. We compare the index based on the first factor of the principal factor analysis with the simple sum of the 8 sub-indices underlying CALURI. For comparability, we normalize the sub-indices and their sum, so all indices in comparison have zero mean and unit variance. GSS = Gyourko, Saiz and Summers (2008)

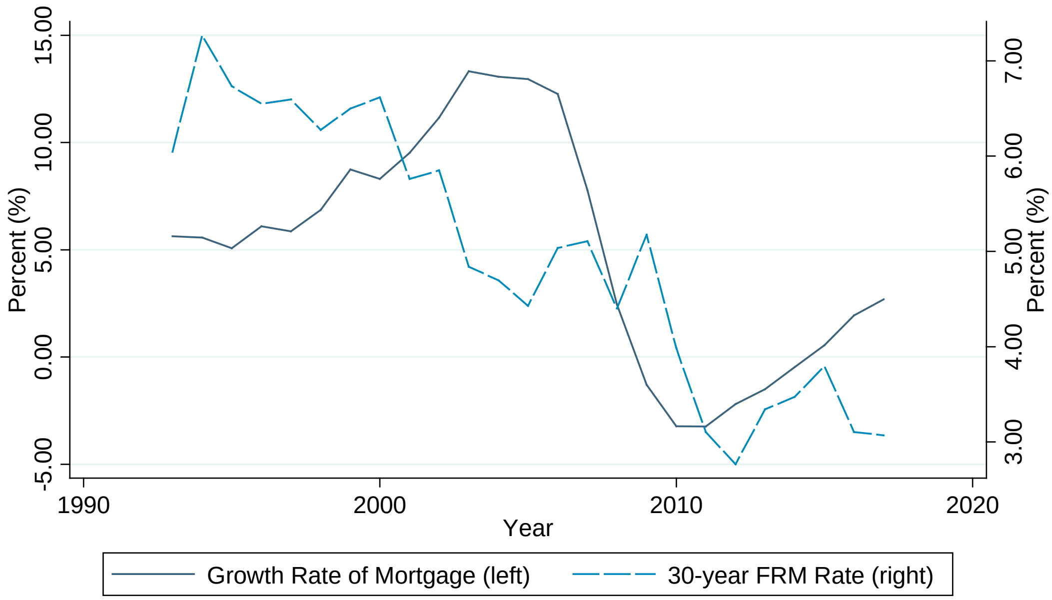
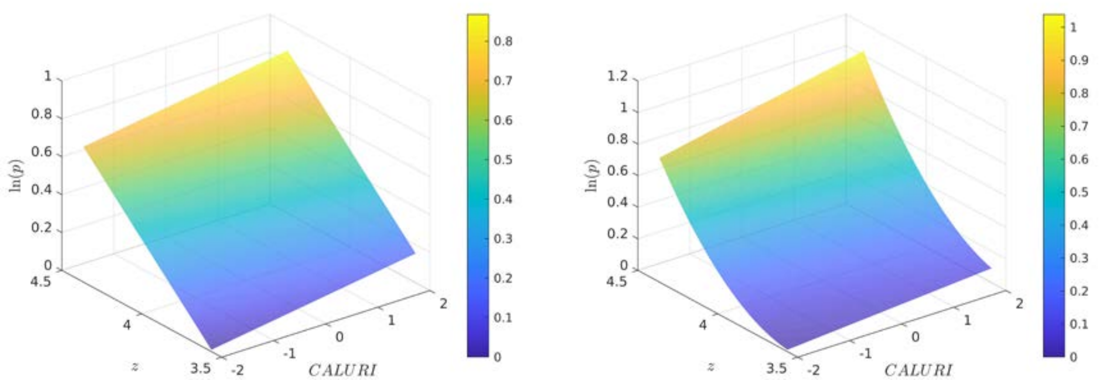


Figure 5: Annual growth rate of the residential mortgage debt of US households and 30-year US average fixed-rate mortgage rate. The mortgage rate has been adjusted for inflation. Source: Z.1 Financial Account Table from the Board of Governors of Federal Reserves and Freddie Mac.



(a) Linear Model (b) Nonlinear Model

Figure 6: the price surface as a function of the log GDP per capita (z) and land use regulation (CALURI). The grid of each dimension is simulated using normal distribution, with the mean and the standard deviation estimated from the data. Grid points within 90% confidence intervals along each dimension are plotted. The parameters are evaluated at the estimated values of Model 4 in panel (a) and Model 7 in panel (b). The min value along the z-axis is normalized to 0.

Figure 7: housing price dynamics of 6 MSAs in California: actual price vs estimated price. The estimation is based on Model 7. The subplots are sorted by the MSA population in 2006 in descending order. The prices are aggregated by year and MSA.

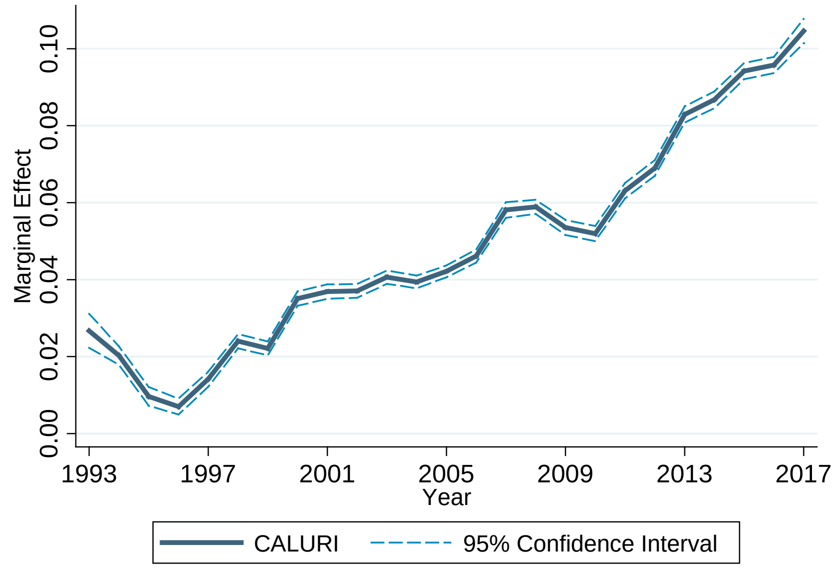


Figure 8: Marginal Effect of CALURI on log housing prices over time. The marginal effect is estimated annually using OLS. The dependent variable is the log housing price. Control variables include CALURI, the log per capita income and its squared term, the number of bedrooms/bathrooms, log mile distance to the nearest core city, the property age, the property type (single family/condo), the property size, the number of days with good air quality, the log mil distance to the Pacific Coast. The dashed lines represent the 95% confidence interval.

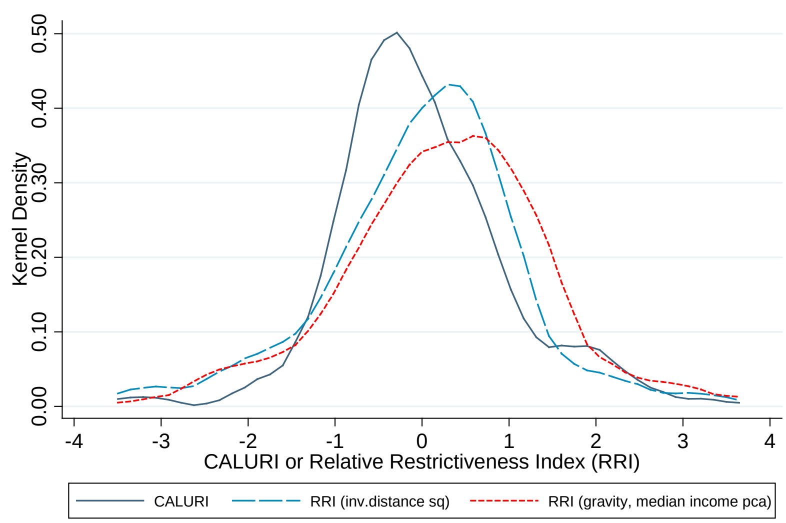
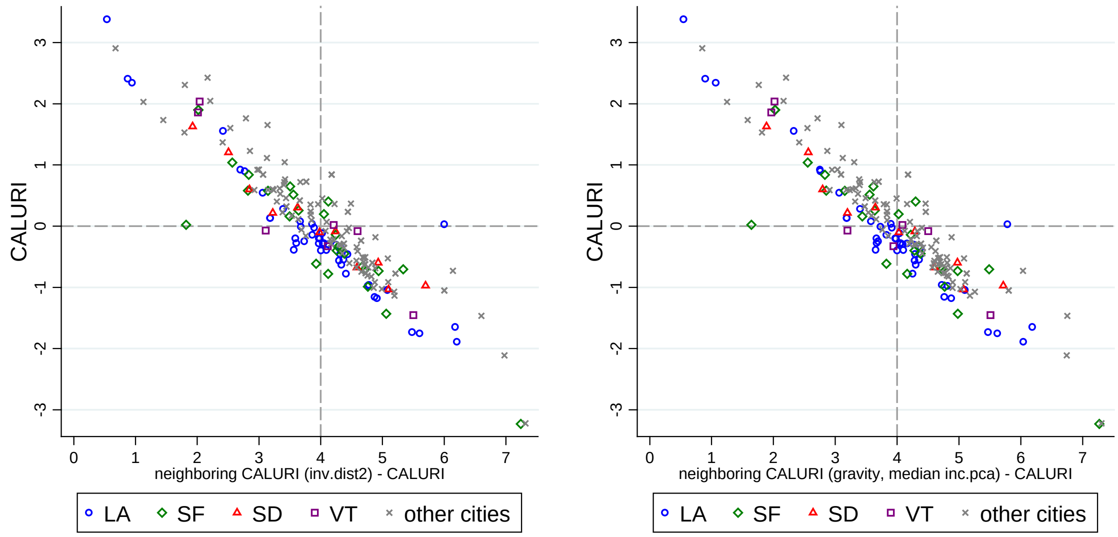


Figure 9: kernel density of CALURI and relative restrictiveness indices (RRI). RRI is defined as the difference between the neighboring regulatory index and CALURI of the city. We report three ways of constructing the neighboring regulatory index, with the weight indicated in the parentheses.



(a) weight: inverse distance sq.

(b) weight: gravity (per capita income*inv. distance sq.)

Figure 10: CALURI vs relative restrictiveness index. Panels (a) and (b) show the scatter plots using different weights in the construction of the neighboring regulatory index. The relative restrictiveness index (RRI) of a city is defined as the difference between the neighboring regulatory index and CALURI of the city. We rescale RRI to the positive real line with the same mean (4) for comparability. We separately mark 4 MSAs (LA = Los Angeles-Long Beach-Anaheim MSA; SF = San Francisco-Oakland-Hayward MSA; SD = San Diego-Carlsbad MSA; VT = Oxnard-Thousand Oaks-Ventura MSA) that are large in terms of and population and the number of cities, and that have high survey response rates in the Wharton Residential Land Use survey (Gyourko, Saiz and Summers, 2008).

Appendix

A.1 Additional Tables and Figures

Table A1. Benchmark Estimation: Marginal Effect of Omitted Control Variables in Table 8

	Model 1 GMM	Model 2 GMM	Model 3 GMM-IV	Model 4 GMM-IV
Bedroom: 1		-0.0391***	-0.0393***	-0.0340***
		(0.003)	(0.003)	(0.003)
Bedroom: 2		-0.169***	-0.169***	-0.165***
		(0.003)	(0.003)	(0.003)
Bedroom: 3		-0.246***	-0.247***	-0.248***
		(0.003)	(0.003)	(0.003)
Bedroom: 4+		-0.325***	-0.325***	-0.329***
		(0.003)	(0.003)	(0.003)
Bathroom: 1		0.0758***	0.0758***	0.0681***
		(0.006)	(0.006)	(0.006)
Bathroom: 2		0.122***	0.123***	0.110***
		(0.006)	(0.006)	(0.006)
Bathroom: 3		0.0885***	0.0910***	0.0744***
		(0.006)	(0.006)	(0.006)
Bathroom: 4+		0.193***	0.196***	0.180***
		(0.006)	(0.006)	(0.006)
log sq.feet		1.066***	1.065***	1.078***
		(0.001)	(0.001)	(0.001)
log miles to		-0.00559***	-0.00529***	-0.00619***
core cities		(0.000)	(0.000)	(0.000)
SFR		-0.0151***	-0.0163***	-0.0285***
		(0.001)	(0.001)	(0.001)
condominium		-0.00744***	-0.00759***	-0.0116***
		(0.001)	(0.001)	(0.001)
Age: 1-5		0.139***	0.139***	0.139***
		(0.001)	(0.001)	(0.001)
Age: 6-10		0.0803***	0.0805***	0.0791***
		(0.001)	(0.001)	(0.001)
Age: 11-20		0.0547***	0.0549***	0.0538***
		(0.001)	(0.001)	(0.001)
Age: 21-30		0.0313***	0.0318***	0.0273***
		(0.001)	(0.001)	(0.001)
Age: 31-40		0.0715***	0.0725***	0.0689***
		(0.001)	(0.001)	(0.001)
Age: 41-50		0.0986***	0.100***	0.101***
		(0.001)	(0.001)	(0.001)
Age: > 50		0.108***	0.110***	0.114***
		(0.001)	(0.001)	(0.001)
growth rate of	3.035***	2.989***	2.966***	2.867***
mortgage debt	(0.007)	(0.006)	(0.006)	(0.006)
30-year FRM	-3.704***	-3.076***	-2.811***	-2.527***
rate	(0.047)	(0.038)	(0.040)	(0.039)
Num. of good days	0.000862***	0.000735***	0.000742***	0.000703***
(air quality)	(0.000)	(0.000)	(0.000)	(0.000)
Log miles to Pacific	-0.107***	-0.121***	-0.122***	-0.124***
coast	(0.000)	(0.000)	(0.000)	(0.000)
Constant	5.577***	-2.028***	-2.152***	-2.317***
	(0.021)	(0.020)	(0.021)	(0.021)
Observations	5,259,215	5,259,215	5,259,215	5,259,215

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. The table reports the omitted control variables and their marginal effects in Model 1-4 in Table 7. The base levels of the factor variables are: no bedroom, no bathroom, property use other than single-family or condo, new property (age is zero). The lag terms of log real GDP per capita and log mean GDP per capita in California are used as IVs of their contemporaneous terms in Models 3-4; the share of high education, the population age and the share of high-jobs are additional IVs of Model 4.

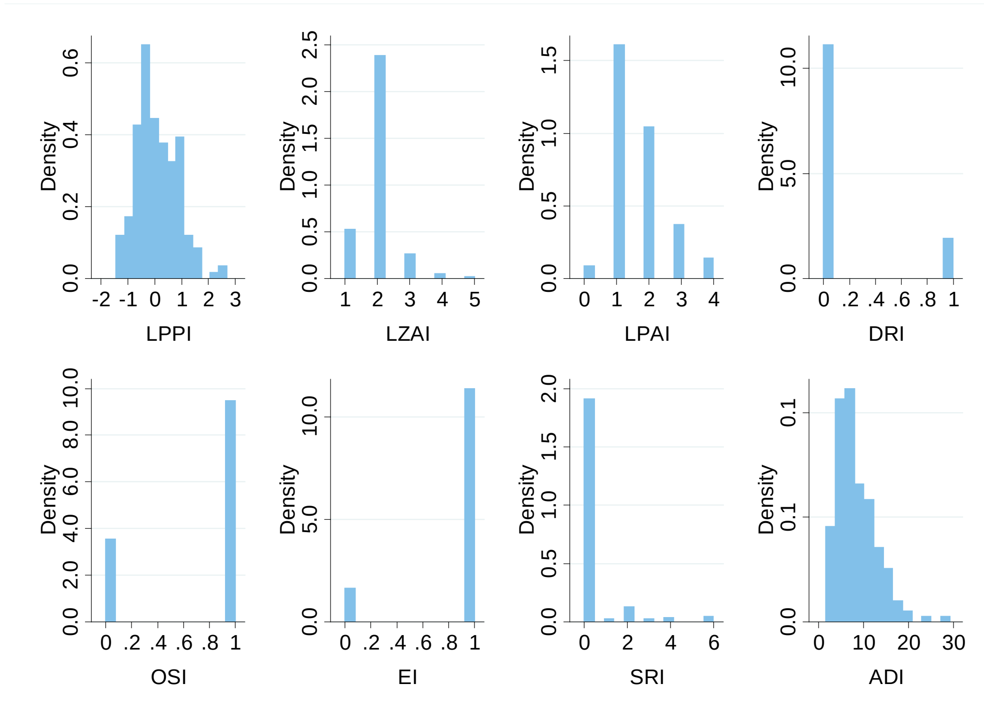


Figure A1: density distribution of the 8 sub-indices underlying the California Land Use Regulation Index (CALURI). Source: Gyourko, Saiz and Summers (2008) and authors' calculation.

A.2 Proof of Uniqueness of the Equilibrium

First, rewrite the market clearing condition of city *j* as follows.

$$q_j = b_j p_j(q_j)^{\frac{1}{1-\theta}}, \text{ where } b_j = \frac{A_0^{\frac{1}{1-\theta}}}{\alpha Y_0 Z_j^{\phi}} \left(\frac{\theta}{c_j}\right)^{\frac{\theta}{1-\theta}} \tag{21}$$

We express p_j as a function of q_j. The equilibrium condition of location choices (5) can be written as

$$q_j x = Z_j^{\phi} p_j(q_j)^{-\alpha}, \text{ where } x = \sum_{k\in S} Z_k^{\phi} r_k^{-\alpha} \tag{22}$$

Combine two equations and eliminate p_j.

$$q_j(x) = Z_j^{\frac{\phi}{\alpha(1-\theta)+1}} b_j^{\frac{\alpha(1-\theta)}{\alpha(1-\theta)+1}} x^{-\frac{1}{\alpha(1-\theta)+1}} \tag{23}$$

For an arbitrary *n*, we can prove that there is a unique set of moving probabilities that solve the system of equations. We can solve *x* from the following equation.

$$\sum_{k\in S} q_j(x) = 1 \tag{24}$$

LHS of (24) is a strictly decreasing function of x, while RHS is a weakly decreasing function of x. There is a unique solution to the equation. Given x, we can use (24) to fully solve the set of moving probabilities.

For the special case of $n = 2$, we can solve the model. With $q_j + q_k = 1$ and $S = \{j, k\}$,

$$q_j = \frac{(Z_j^{\phi})^{1-\lambda} b_j^{\lambda}}{(Z_j^{\phi})^{1-\lambda} b_j^{\lambda} + (Z_k^{\phi})^{1-\lambda} b_k^{\lambda}}, \text{ where } \lambda = \frac{\alpha(1-\theta)}{\alpha(1-\theta)+1} \tag{25}$$

Combined with (21), the log housing price can be expressed as (10).

To linearize the nonlinear term associated with the moving probability in (10), we conduct the following approximation to the function ln(1+exp(x)) at the mean $x = 0$.

$$\begin{aligned} &(1-\theta)\ln\left[1+e^{(2\lambda-1)\phi(z_j-z_k)+\frac{\theta}{1-\theta}\lambda(\ln\tau_j-\ln\tau_k)}\right] \\ &\approx \tfrac{1}{2}\{(1-\theta)(2\lambda-1)\phi(z_j-z_k)+\theta\lambda(\ln\tau_j-\ln\tau_k)\}+(1-\theta)\ln 2 \end{aligned} \tag{26}$$

We confirm numerically that the exact nonlinear function and the approximated linear functions are very close. In the relevant domains of the city income z_j and regulation τ_j, the exact nonlinear function has a very small curvature, so the approximation works very well in our case.

A.3 CALURI by MSA and City

Table A2. City and CALURI

MSA and City	CALURI	MSA and City	CALURI
Bakersfield	0.291	Signal Hill city	-0.203
McFarland city	1.735	Redondo Beach city	-0.245
Bakersfield city	-0.308	Pico Rivera city	-0.279
Delano city	-1.052	Lakewood city	-0.279
Chico	0.190	Tustin city	-0.284
Orland city	0.721	La Palma city	-0.289
Paradise town	0.527	Palmdale city	-0.297
Willows city	-0.163	Claremont city	-0.302
Gridley city	-0.288	Los Alamitos city	-0.351
Chico city	-0.343	Commerce city	-0.385
Fresno	1.032	Whittier city	-0.389
Huron city	2.908	South Pasadena city	-0.396
Selma city	2.429	Lancaster city	-0.455
Kingsburg city	0.841	La Canada Flintridge city	-0.459
Fresno city	0.452	Avalon city	-0.544
Parlier city	0.369	Hermosa Beach city	-0.561
Reedley city	0.236	Alhambra city	-0.631
Hanford-Corcoran	-1.280	Calabasas city	-0.775
Corcoran city	-0.508	Carson city	-0.962
Avenal city	-2.112	Huntington Beach city	-0.975
Los Angeles-Long Beach-Anaheim	-0.195	La Habra city	-1.042
Los Angeles city	3.382	Agoura Hills city	-1.157
Glendora city	2.408	Palos Verdes Estates city	-1.178
El Monte city	2.342	Covina city	-1.648
San Fernando city	1.558	Montebello city	-1.730
Irvine city	0.924	Santa Ana city	-1.751
Seal Beach city	0.897	Baldwin Park city	-1.889
Brea city	0.546	Arcadia city	NA
Pomona city	0.322	San Marino city	NA
Compton city	0.280	**Madera**	-0.772
La Habra Heights city	0.131	Mammoth Lakes town	-0.623
El Segundo city	0.077	Chowchilla city	-0.772
Rancho Santa Margarita city	0.037	**Merced**	0.830
Beverly Hills city	0.032	Los Banos city	2.046
Anaheim city	-0.008	Merced city	1.231
Dana Point city	-0.025	Dos Palos city	0.728
San Clemente city	-0.115	Gustine city	-0.081
Gardena city	-0.142	**Modesto**	-0.036
Fountain Valley city	-0.198	Waterford city	0.458
Long Beach city	-0.198	Ceres city	-0.684

Table A2. City and CALURI (continued)

MSA and City	CALURI	MSA and City	CALURI
Napa	0.414	Rancho Cordova city	0.070
Calistoga city	1.114	West Sacramento city	-0.353
St. Helena city	0.363	Rocklin city	-0.510
American Canyon city	0.242	Placerville city	-1.072
Oxnard-Thousand Oaks-Ventura	0.254	**Salinas**	-0.294
Santa Paula city	2.037	Carmel-by-the-Sea city	2.031
San Buenaventura (Ventura) city	1.861	Soledad city	0.226
Camarillo city	0.020	Greenfield city	-0.914
Oxnard city	-0.071	Seaside city	-1.466
Ojai city	-0.081	**San Diego-Carlsbad**	-0.253
Simi Valley city	-0.327	Encinitas city	1.630
Port Hueneme city	-1.453	Coronado city	1.207
Redding	-0.307	Del Mar city	0.599
Shasta Lake city	0.173	San Diego city	0.303
Anderson city	-0.584	El Cajon city	0.217
Weed city	-0.768	Vista city	-0.086
Riverside-San Bernardino-Ontario	-0.081	Lemon Grove city	-0.102
Beaumont city	1.761	National city	-0.596
Banning city	1.654	Poway city	-0.676
Rancho Mirage city	0.921	Solana Beach city	-0.972
Riverside city	0.842	Santee city	-1.035
Coachella city	0.675	**San Francisco-Oakland-Hayward**	-0.219
Needles city	0.617	Portola Valley town	1.899
Chino city	0.590	San Francisco city	1.040
Corona city	0.419	Belmont city	0.839
Loma Linda city	0.402	Redwood city	0.648
Norco city	0.353	Hercules city	0.582
Palm Desert city	-0.180	San Leandro city	0.578
Yucaipa city	-0.236	Larkspur city	0.515
Chino Hills city	-0.287	Woodside town	0.402
Blythe city	-0.299	Martinez city	0.256
Colton city	-0.599	Corte Madera town	0.196
Montclair city	-0.625	San Ramon city	0.159
Barstow city	-0.674	Burlingame city	0.022
Hesperia city	-0.745	Mill Valley city	-0.139
Big Bear Lake city	-1.136	Fremont city	-0.338
Canyon Lake city	-3.222	Brentwood city	-0.397
Sacramento-Roseville-Arden-Arcade	-0.001	Pittsburg city	-0.450
Folsom city	1.370	Millbrae city	-0.614
Lincoln city	0.112	Dublin city	-0.664

Table A2. City and CALURI (continued)

MSA and City	CALURI	MSA and City	CALURI
Sausalito city	-0.700	Santa Maria city	-0.519
Menlo Park city	-0.703	**Santa Rosa**	0.653
Pinole city	-0.732	Sonoma city	2.309
Piedmont city	-0.778	Rohnert Park city	0.719
San Pablo city	-0.987	Windsor town	-0.027
Emeryville city	-1.430	**Stockton-Lodi**	-0.110
Hillsborough town	-3.232	Ripon city	0.592
San Jose-Sunnyvale-Santa Clara	-0.657	Jackson city	-0.219
Campbell city	-0.158	Manteca city	-0.407
Santa Clara city	-0.605	Lodi city	-0.769
Morgan Hill city	-0.824	**Vallejo-Fairfield**	0.187
San Jose city	-1.007	Benicia city	0.187
San Luis Obispo-Paso Robles-Arroyo Grande	0.531	**Visalia-Porterville**	-0.292
San Luis Obispo city	1.603	Visalia city	0.606
Morro Bay city	1.046	Exeter city	-0.060
Arroyo Grande city	0.590	Woodlake city	-0.079
Grover Beach city	-0.526	Farmersville city	-0.674
Santa Cruz-Watsonville	-0.036	Porterville city	-0.806
Scotts Valley city	0.358	**Yuba City**	0.849
Capitola city	-0.731	Live Oak city	1.532
Santa Maria-Santa Barbara	-0.158	Williams city	0.922
Buellton city	0.098	Yuba city	-1.026

Note: MSAs are sorted in alphabetic order. Within each MSA, cities are sorted by CALURI in descending order. CALURI is defined as the first factor using the principal factor analysis. 8 sub-indices that have city-level variations from the Wharton Residential Land Use Survey are used: local political pressure index (LPPI), local zoning approval index (LZAI), local project approval index (LPAI), density restriction index (DRI), open space index (OSI), exactions index (EI), supply restriction index (SRI), approval delay index (ADI). Source: Gyourko, Saiz and Summer (2008) and authors' calculation.

Table A3. Survey Response Rates by CBSA in California

	City and Town			Principal City		
CBSA (MSA/μMSA)	CA	GSS	%	CA	GSS	%
Bakersfield	11	3	27	1	1	100
Chico	5	3	60	1	1	100
Clearlake	2	1	50	1	0	0
Crescent City	1	1	100	1	1	100
El Centro	7	0	0	1	0	0
Eureka-Arcata-Fortuna	7	1	14	3	1	33
Fresno	15	6	40	1	1	100
Hanford-Corcoran	4	2	50	2	1	50
Los Angeles-Long Beach-Anaheim	122	48	39	25	13	52
Madera	2	1	50	1	0	0
Merced	6	4	67	1	1	100
Modesto	9	2	22	1	0	0
Napa	5	3	60	1	0	0
Oxnard-Thousand Oaks-Ventura	10	7	70	4	3	75
Red Bluff	3	1	33	1	0	0
Redding	3	2	67	1	0	0
Riverside-San Bernardino-Ontario	52	20	38	9	3	33
Sacramento--Roseville--Arden-Arcade	19	6	32	5	2	40
Salinas	12	4	33	1	0	0
San Diego-Carlsbad	18	11	61	4	2	50
San Francisco-Oakland-Hayward	65	25	38	12	4	33
San Jose-Sunnyvale-Santa Clara	17	4	24	7	2	29
San Luis Obispo-Paso Robles-Arroyo Grande	7	4	57	2	1	50
Santa Cruz-Watsonville	4	2	50	2	0	0
Santa Maria-Santa Barbara	8	2	25	3	1	33
Santa Rosa	9	3	33	2	0	0
Sonora	1	0	0	0	0	0
Stockton-Lodi	7	3	43	1	0	0
Susanville	1	1	100	1	1	100
Truckee-Grass Valley	3	0	0	2	0	0
Ukiah	4	1	25	1	1	100
Vallejo-Fairfield	7	1	14	2	0	0
Visalia-Porterville	8	5	63	2	2	100
Yuba City	4	2	50	1	1	100
Total	458	179	39	103	43	42

Note: the list of Core Based Statistical Areas (CBSA) includes both MSAs and μMSAs. There are 482 jurisdictions in California, with 458 tied to the CBSA codes in California. "CA" and "GSS" counts the total number of cities and towns in California (CA) and in the sample of Gyourko, Saiz and Summers (2008) (GSS) respectively. The columns with "%" calculate the city share of GSS sample in California (response rate). The definition of the principal cities is based on the historical delineation files of the Principal cities of metropolitan and micropolitan statistical areas (2006) from the Census Bureau. The definition of CBSA is based on 2010 Geographic Terms and Concepts from the Census Bureau.

A.4 Data Filtering and Construction of ZTRAX Variables

The Whole ZTRAX database consists of two parts: ZTrans (transaction data) and ZAsmt (assessment data) that can be linked by a unique parcel ID. For most states, the sample prior to 2005 are scarce; for California, the database can trace back to transactions as early as 1993. I first restrict the sample to the transaction with the sales prices more than 5,000 US dollars in California. California data before 1993 (inclusive) is extremely sparse, so our ZTRAX data starts from 1993:M1 and ends in 2017:M6. For the other US states, the quality of data before 2005 is generally worse than that after the 2005. California data allows us to examine the housing prices and property characteristics in a much longer horizon.

We keep residential properties only and drop any commercials, manufactural, and foreclosure sales. Based on the Property Use Standard Code and Assessment Land Use Standard Code, we identify and focus on the residential types including single family residentials, townhouses, cluster homes, condominiums, cooperatives, planned unit developments and those inferred as single family residentials by Zillow. A transaction can involve multiple parcels, we focus on transactions with a single parcel only. We only keep the transactions that can be linked to the housing properties in the assessment data. About 89% of the transactions are matched to the assessment files.

The data fields of the housing data include: transaction date, geographic location (county, city, CBSA, address longitude and latitude), the sales prices, the number of bedrooms and bathrooms, the year a property was built, the square foot of a property and the miles to the nearest core cities. There are other housing characteristics available in the database, but they are in general not commonly populated.

There is no separate field to directly observe the size of a property, so we construct the field as follows. We are able to observe the following fields relevant to the size of a property: building area living, building area finished, effective building area, gross building area, building area adjusted, building area total, building area finished living, base building area, heated building area. To take the maximum of the fields above and define it as the square footage of a property.

The miles of a property to the nearest core cities is constructed as follows. We first identify the CBSA where a property is located. We use the leading principal cities listed in the name of an MSA and geocode the city centers using the application program interface (API) of Google Map. We calculate the great-circle distance in miles from each property to the center of each leading principal city in the CBSA and define the minimum as the distance to the principal city. A small number of cities are not assigned to any CBSA. We thus geocode the distance from the properties in each of the cities to the nearest leading principal cities in all CBSAs in California using the API of Google Map.[52] We assign these cities to the nearest MSAs, so they don't fall out of sample in the analysis.

[52] 6 cities whose fips county codes don't fall in any MSA in California are assigned to the nearest metropolitan statistical area. They are Jackson City, Williams City, Orland City, Willows City, Mammoth Lakes Town, and Weed City.

The number of annual transactions in California ranges from 100,000 to 600,000, depending on the year. There are about 13 million transactions in total from about 1,400 cities available to be matched to the Wharton Land Use Survey data.

A.5 Foundation of the Interactive and Quadratic Effects

A.5.1 Foundation of the Interactive Effect

We establish how our estimation equation relies on the assumption that the measured impact of regulation on housing production is correlated with the amenity level. Motivated by the finding in the literature, we generalize the log marginal cost of housing production with the following multiplicative form.[53] [54]

$$\ln c_j = (\delta_1 z_j + \delta_0)\ln \tau_j + \ln c_0 \tag{27}$$

The parameters δ_1 and δ_0 control the sensitivity of the marginal cost. With $\delta_0 = 1$ and $\delta_1 = 0$, we go back to the benchmark case. When $\delta_1 > 0$ (we show it is the case), the housing supply exhibits a higher price impact in cities with high income and amenity demand. In estimation, we impose a parametric restriction to focus on the following class of the models that include the benchmark model as a special case.

$$\delta_1 E_t(z_{0t}) + \delta_0 = 1 \tag{28}$$

For a property located in an MSA with the log per capita income equal to $E_t(z_{0t})$, *ceteris paribus*, the marginal effect of regulation intensity will be identical in the estimation equations with and without an interactive term. For computation, there are two parameters with one degree of freedom. The new estimation equation will be similar to (12), but with an additional interactive term of CALURI and the log per capita income.

A.5.2 Foundations of the Quadratic Effect

We extend the assumption of constant income elasticity of housing demand. The extension results in the quadratic term of the log per capita income in estimation.[55]

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[53] Glaeser, Gyourko and Saks (2005a) find that the likelihood to build new housing units, an inverse measure of time cost, is lower in wealthier communities. Homeowners in the wealthy communities may use time to influence local planning (Gyourko and Molloy, 2015). Fischel (2001) brings about the homevoter hypothesis that homeowners in wealthy communities have stronger incentive to protect local amenities capitalized in housing values.

[54] If the impact of the log amenity comes into the marginal cost in an additive form. The parameters δ_1 and δ_0 will remain unidentified in estimation.

[55] We leave out the quadratic effect of the regulation intensity in the section, because we don't find the quantitatively important quadratic effect along the dimension. Moreover, the regulation intensity is an index we construct from sub-indices. We take the stand that the index construction should pick up the high-order effects, if there is any.

The parameter ϕ in the benchmark model has the interpretation of the income elasticity of hosing demand. The household income adjusted by demand shifter can be written as $\exp(\phi z)$. We extend the linear form to the quadratic form in the power term.

$$\exp(\phi_0 + \phi_1 z + \phi_2 z^2) = Z \exp(\phi_0) Z^{\phi_2 z + \phi_1 - 1} \tag{29}$$

where the last term on the right side is the demand shifter and $2\phi_2 z + \phi_1$ will be the income elasticity of housing demand. With $\phi_0 = 0$ and $\phi_2 = 0$, we go back to the benchmark case. When $\phi_2 > 0$ (we show it is the case), the income elasticity is higher for wealthier cities.

In the estimation, we impose two parametric restrictions to focus on the following class of models that include the benchmark model as a special case.

$$\begin{aligned} \phi_{avg} &= 2\phi_2 E_t(z_{0t}) + \phi_1 \\ \phi_{avg} E_t(z_{0t}) &= \phi_0 + \phi_1 E_t(z_{0t}) + \phi_2 [E_t(z_{0t})]^2 \end{aligned} \tag{30}$$

The parameter ϕ_{avg} is the average income elasticity of housing demand according to the first restriction. The second restriction indicates that when the city income is equal to $E_t(z_{0t})$, the elasticity of amenity demand is identical in the benchmark and the extended model.

To focus on the marginal effect of regulation and per capita income on housing prices, we further make an assumption that a household uses the average elasticity ϕ_{avg} in the location choice problem, which is the same as the benchmark case. The assumption allows us to focus on the quadratic term of the log per capita income as an additional term in the estimation equation (12).[56]

A.6 Structural Parameter Estimates

In Table A4, we report the estimation of the structural parameters. Without housing characteristics controlled in Model 1, we tend to underestimate θ by 30%, but to overestimate ϕ. GMM-IV estimations produce comparable estimated parameters in Models 3 and 4. Compared with Model 2, Model 4 which treats contemporaneous per capita income as endogenous yield bigger estimated values of ϕ and θ.

[56] What the approximation assumption leaves out is the interactive effect of the GDP per capita and the mean GDP per capita of California, and the quadratic effect of the latter term.

Table A4. Benchmark Estimation: Structural Parameters

	Model 1 GMM	Model 2 GMM	Model 3 GMM-IV	Model 4 GMM-IV
θ	0.064***	0.086***	0.087***	0.090***
	(0.001)	(0.000)	(0.000)	(0.000)
λ	1.085***	1.022***	1.039***	1.043***
	(0.001)	(0.001)	(0.001)	(0.001)
ϕ	1.946***	1.956***	1.991***	2.022***
	(0.005)	(0.004)	(0.005)	(0.005)

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. The lag terms of log real GDP per capita and log mean GDP per capita in California are used as IVs of their contemporaneous terms in Models 3-4; the share of high education, the population age and the share of high-jobs are additional IVs of Model 4.

In Table A5, we replicate the GMM estimations in Table 8, but instead use WALURI as the regulatory index instead. Compared to CALURI based on California cities, WALURI is estimated nationally from more than 2,500 jurisdictions.

Table A5. Benchmark Estimation with WRLURI: Marginal Effect

	Model 1 GMM	Model 2 GMM	Model 3 GMM-IV	Model 4 GMM-IV
WRLURI	0.0676***	0.0730***	0.0728***	0.0755***
	(0.000)	(0.000)	(0.000)	(0.000)
log GDP per	0.767***	0.863***	0.847***	0.847***
capita	(0.002)	(0.001)	(0.001)	(0.001)
log Avg.	1.053***	0.920***	0.966***	0.986***
GDP per cap	(0.005)	(0.004)	(0.004)	(0.004)
Observations	5,259,215	5,259,215	5,259,215	5,259,215

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. The table replicate the specifications in Table 8 using WRLURI instead as the regulatory measure. Omitted control variables in Models 2-4: the number of bedrooms, the number of bathrooms, log mile distance to the nearest core city, the property age, the property type (single family/condo), the property size, the mortgage growth rate, the 30-year FRM rate, log mile distance to the Pacific coast, the number of good days (air quality). The lag terms of log real GDP per capita and log mean GDP per capita in California are used as IVs of their contemporaneous terms in Models 3-4; the share of high education, the population age and the share of high-jobs are additional IVs of Model 4. Models are estimated using GMM.

In Table A6, we report the parameter estimates for Table 10. The average income elasticity of amenity demand is adjusted upward from 1.022 in Model 4 to the 1.251 in Model 7. The coefficient of the quadratic term ϕ_2 is positive in Model 7, indicating that the income elasticity of housing demand increases with income.

Table A6. Estimation with Non-Linear Effects: Structural Parameters

	Model 4 GMM-IV	Model 5 GMM-IV	Model 6 GMM-IV	Model 7 GMM-IV
θ	0.090***	0.092***	0.088***	0.093***
	(0.000)	(0.000)	(0.000)	(0.000)
λ	1.043***	1.044***	0.955***	0.953***
	(0.001)	(0.001)	(0.001)	(0.001)
δ_0	1.000***	-1.236***	1.000***	-3.183***
	(0.000)	(0.045)	(0.000)	(0.047)
δ_1	0.000***	0.562***	0.000***	1.052***
	(0.000)	(0.011)	(0.000)	(0.012)
ϕ_0	0.000***	0.000***	17.174***	18.179***
	(0.000)	(0.000)	(0.067)	(0.068)
ϕ_1	2.022***	2.012***	-6.384***	-6.890***
	(0.005)	(0.005)	(0.033)	(0.034)
ϕ_2	0.000***	0.000***	1.086***	1.149***
	(0.000)	(0.000)	(0.004)	(0.004)
ϕ_{avg}	2.022***	2.012***	2.252***	2.251***
	(0.005)	(0.005)	(0.005)	(0.005)

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010.