Local Land Use Regulation and Housing Prices: How Relative Restrictiveness and Income Matter*

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Abstract

Local land use regulation may restrict housing supply, with more stringent regulation associated with higher local housing prices, as demonstrated by the empirical literature. If so, demand spillover to surrounding communities, may moderate local house price increases. We develop and test a model for how spillovers affect local price outcomes. Using data for California, we show that relative income and relative restrictiveness matter for the impact of local regulation on local housing prices.

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1. Introduction

Land use regulations may restrict local housing supply, and, in so doing, raise local housing prices, as demonstrated by a large empirical literature. However, given that household location choice extends beyond the boundaries of a single locality, a locality's restrictive land use regulation may lead to a spillover effect that limits the local rise in housing prices, as it increases demand elsewhere. In this paper, we develop a parsimonious model to empirically test for this effect, along with the direct effect of regulation. The model incorporates relative regulation and relative income.

Tighter regulation may cause a housing demand reallocation from the city imposing land use restrictions to neighboring cities, and, beyond; such "spillovers" depend on alternative communities' regulatory regime and attractiveness, here measured by income. Regulation that covers multiple localities may limit spillovers. Moreover, across localities, regulation may have different impacts depending on the extent of spillovers.

Most empirical studies do not measure spillover effects. Rather empirical studies of land use regulation generally regress housing prices against a regulatory index, without including surrounding regulatory regimes or income. For example, Jackson (2018) tests for the impact of regulation, using a pooled sample of price indices for California over three years (2000, 2006, and 2012) and finds 5% higher housing prices attributable to a one standard deviation increase in an index of regulation. An earlier paper by Quigley, Raphael and Rosenthal (2008) for the San Francisco Bay Area finds a regulatory effect on housing prices of 1% to 2% based on OLS and 3.8% to 5.3% when regulation is instrumented by political preference. We replicate these studies, but also ask whether an indirect spillover effect which varies with relative income and relative restrictiveness influences these results.

We formalize and test for the impact of regulation through a structural general equilibrium model with household mobility. Tighter local regulation in a locality is hypothesized to increase housing supply costs, and housing prices, all else equal, with the impact varying with the potential for spillovers which depends on surrounding localities' regulation as well as per capita income. That is, more stringent regulation leads to a leftward shift in the local housing supply curve and higher housing prices, but the equilibrium impact on prices depends on demand curve shifts due to the displacement of local demand, through household location choice.

Using a structural approach, we decompose the total effect of local regulation on local housing prices into a direct (partial equilibrium, PE, or home regulatory) effect and an indirect (general equilibrium, GE, or spillover) effect, separating the local price impact due to decreased supply and the counteracting decreased demand. We anticipate that the ratio of GE to PE effects will be lower for relatively high-income localities and for relatively less regulated localities.

We use housing price transaction data, adjusted for housing characteristics for all residential sales in California from 1993 to 2017, available from Zillow. We measure regulation with the Wharton

Regulatory Index (Gyourko, Saiz and Summers, 2008) fielded in 2006 for cities in California, a state with considerable city-level variation in regulatory stringency (Fischel, 1995). We use annual MSA level per capita income to measure demand and accompanying macro variables. We examine the endogeneity of per capita income, using demographic information from the American Community Survey (ACS) and regulation, using voting patterns. We also use a more recent regulatory survey, the Terner Center Land Use Survey fielded in 2017 (Mawhorter and Reid, 2018) to test robustness of results.

Ideally, we would like to have data on regulatory restrictiveness for all jurisdictions over time.[1] We have broad (albeit not complete) coverage for regulation in localities in the Greater Los Angeles area (as well as 5-year average income data from ACS). The Wharton Regulatory index coverage for the rest of the state is less complete; therefore, we test for the impact of local regulation on local housing prices and use the rest of the state of California as the alternative location to incorporate household choice.

These structural estimations for the state of California replicate, qualitatively, earlier studies' results for the direct impact of regulation on housing prices in California. We test for the impact of income on housing prices and for how regulation interacts with income, finding as expected, that regulation has a larger impact on home housing prices in high-income metro areas. We estimate and find evidence of (increasing) time-varying effects of regulation. We also simulate the impact of regulatory change, assuming the case of reducing regulation to that of the mean and least regulated locality in the MSA Despite the lack of spatial specificity, we find evidence of spillover effects that vary with MSA characteristics.

We account for city-specific relative regulatory restrictiveness for the Greater Los Angeles area (Los Angeles, Orange and Ventura counties), using 5-year estimates of income for 2012 to 2016. We define an index of relative restrictiveness that varies for each city, using a gravity weighting model, for Greater LA. We find similar estimates for the size of the direct (total) effect of one SD in regulation in LA as we do in the state-wide empirical analysis. But we show here that this total effect is an outcome of (given the better data) a now larger measured partial equilibrium and general equilibrium effect We show that local regulation's effect on housing prices depends on the stringency of local regulation relative to regulation in surrounding communities. The contribution of the paper is the identification of spillover effects which vary with relative restrictiveness and relative income in both of these settings.

The paper is organized as follows. Section 2 reviews the literature. Section 3 sets up the general equilibrium model of regulation and housing markets. Section 4 describes the data and summary statistics. Section 5 shows results for California. Section 6 shows results for Greater Los Angeles. We discuss in Section 7 and conclude in Section 8.

[1] There appear to be no repeatedly fielded publicly available surveys. However, the Wharton Regulatory Index has been fielded again recently. Preliminary comparisons show for cities surveyed twice, the results are not substantially different (Gyourko and Krimmel, 2019).

2. Literature Review

The theoretical literature shows how local land use regulation restricts housing supply and raises prices. (Brueckner 1995). Quigley and Rosenthal (2005) review the relevant empirical literature through 2005. We update this review with a summary of recent empirical studies in Table 1. 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), generally use housing prices or housing price indexes as the dependent variable with explanatory variables including controls (*e.g.* housing and neighborhood characteristics). Most studies 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 (Table 1).

To construct measures of local land use regulation, most of the studies use locally fielded surveys and construct indices and sub-indices (*e.g.* on approval delays or open space requirements), either by implementing a standardized sum of regulatory measures (Quigley and Raphael, 2005; Ihlanfeldt, 2007; Glaeser and Ward, 2009; Kok et al, 2014; Jackson, 2018), or by principal factor analysis (Quigley et al, 2008; Huang and Tang, 2012; Albouy and Ehrlich, 2018). Hilber and Robert-Nicoud (2013) discusses the benefit of using a single aggregate index compared to a number of sub-indices and the literature generally follows this approach. 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. Across these studies the impact of one standard deviation increase in regulation on housing prices is generally estimated to be around 5%, with the estimate for the impact of regulation in Boston an outlier at 10%.[2]

The earliest of the surveys, the Wharton Survey of Planning and Policy, was constructed by Linneman, Summers, Brooks and Buist (1990) followed on by a survey done for California (Glickfeld and Levine, 1992). However, the data from these studies are no longer available. Quigley, Raphael and Rosenthal (2008) developed the Berkeley Land Use Survey, for cities in the San Francisco Bay Area. Most recently, Jackson (2018) administered a separate California land use survey. The data from these studies are not publicly available. Mawhorter and Reid (2018) fielded the recent Terner Center land use survey for California, which is available and which we use to test for the robustness of our results.

The main regulation index we use is compiled from the Wharton Residential Land Use Regulation Index (WRLURI), fielded in 2006 (Gyourko, Saiz and Summers, 2008).[3] WRLURI is a national survey

[2] Glaeser and Ward's study on the Boston metro area from 2000 to 2005 uses a non-standardized index of regulation and finds a 10% impact on housing prices.
[3] See Gyourko and Malloy (2015) for a comparative discussion of these indices.

with responses from 2,649 jurisdictions and the index is based on principal factor analysis of sub-indices which is used to construct a single regulatory measure for each reporting locality.[4] We develop the California Land Use Regulation index, or CALURI, based on WRLURI. All the surveys including the WRLURI survey suffer from non-universal coverage and from the inability to survey the same communities over time.

There are other approaches to show the impact of regulation on house prices. In a recent paper, Albouy and Ehrlich (2018) construct a regulation cost index, based on WRLURI, and find that this explains two-fifths of the variance between input costs and output prices, thus demonstrating the impact of home regulation on housing prices after other costs are calculated. This result is a larger impact than the literature generally finds and is consistent with our results. Nonetheless, our model implies that the direct impact of WRULRI on housing prices is underestimated, since with a higher observed WRLURI, all else equal, the land value in that locality will be lower due to a spillover to surrounding localities.[5] Another branch of studies (Turner et al, 2014; Severen and Platinga, 2018), also complementary to ours, examines land or housing price gradient within certain distances from the regulatory boundaries. Those studies decompose the total effect of regulation into a local effect that purely reflects the difference in regulation and results in price discontinuity at the boundaries. Properties on the boundaries enjoy the same amenities but differ in regulation, leading to an identification of the local effect through the discontinuity of regulatory regimes.

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 and drive out potential residents, resulting in high prices elsewhere. Pollakowski and Wachter (1990) examine a single county and show 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.[6] If such effects exist, more generally, pricing outcomes in the home community depend not only on the home regulation but that of neighboring communities as well. If so, the same level of

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[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. Gyourko and Krimmel (2019) conduct a follow-up survey of the 2006 Wharton survey, but only one third are replicated with a 25% response rate which limits replicability.

[5] We consider a model extension in the appendix where regulation may have a direct effect on housing demand, an idea incorporating what Albouy and Ehrlich (2018) propose.

[6] Pollakowski and Wachter (1990), Brueckner (1990), and Engle, Navarro and Carson (1992) discuss the 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.

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 structural model to identify such effects.[7]

3. Model

We set up a spatial general equilibrium model with households who choose locations and with housing suppliers whose costs vary with local regulation. Location choices balance the location benefit of income and the cost of living captured by local housing prices, as impacted by regulation. We solve for equilibrium housing prices as a function of land use regulation and income and identify price effects on the home and the surrounding markets.

3.1 A Stylized Example

Figure 1a illustrates the model through a stylized example with two housing markets. Starting from an initial equilibrium denoted by E_0, land use regulation tightens in Market 1 and remains unchanged in Market 2. The tightening of 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, shown as a partial equilibrium effect. Households re-evaluate their consumption and location choices, leading to a reallocation of housing demand between the two markets, as shown by a leftward shift in the demand curve in Market 1 and a rightward shift in the demand curve in Market 2. Eventually, both housing markets will settle at a new equilibrium denoted by E_2, with the equilibrium demand curve in Market 1 incorporating the equilibrium reallocation of demand to Market 2. The direct effect or total change in the equilibrium price in Market 1 is decomposed into a partial equilibrium (PE) and counteracting general equilibrium (GE) effect. The GE effect lessens the PE effect resulting in a lower impact of home regulation on home housing prices.

In an extreme case, shown in Figure 1b, the GE effect cancels out the PE effect, leading to zero total effect of regulation. Regulation in a local community results in a movement out of households to surrounding communities with the supply outside the local community effectively infinitely elastic and hence, with no consequence to local (quality adjusted) housing prices.[8]

On the other hand, an increase in regulatory restrictiveness in both localities, shown in Figure 1c, results in a PE effect which is not offset by GE effects and therefore is equal to the direct effect since both markets adopt the greater supply restriction. There is no incentive to move as prices have increased identically in both localities. This simplified model points to the importance of the question, is a

[7] Spatial equilibrium models in urban economics date back to the pioneering work by Rosen (1979) and Roback (1982).
[8] Housing prices could increase due to an amenity effect, say from lower density, ignored in this example.

regulatory shift imposed in one or many communities for the impact of regulation (or deregulation) on local housing prices.

To identify partial and general equilibrium effects in the data, we develop a parsimonious general equilibrium model in which households and housing suppliers optimize location choices and production decisions. We estimate the model for cities and metro areas throughout California and for the Greater Los Angeles area.

3.2 Household Optimization

Households indexed by i value the non-durable consumption υ 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.[9] [10]

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

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 as 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 individual household income Y_i, a city-specific income Z_j, and a demand shifter A_j.[11] Two income components, Y_i and Z_j, are assumed independently distributed and are multiplicative for tractability of analysis.[12] The demand shifter A_j may be associated with amenity effects and agglomeration effects in a reduced form. We assume A_j is a function of city income Z_j.[13]

The parameter ϕ controls the income elasticity of housing demand. The parameter α measures the housing consumption share relative to the numeraire 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

[9] In the appendix, we a model extension in which regulation have a direct effect on demand, for example, due to the amenity effect. We estimate the extended model and find the direct impact of regulation on the housing demand is economically small. We thus focus on the direct effect on housing supply in the main text.

[10] We assume that the expenditure on housing is linear in rent. There are models in the literature with non-linear pricing to capture housing quality (Landvoigt et al, 2015). We assume linear pricing for tractable analysis. We include housing characteristics to control housing quality in estimation.

[11] 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.

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

[13] In the appendix, we allow regulation as an additional determinant of the demand shifter to account for the possible direct effect of regulation through an amenity channel. We find that the estimated amenity effect of regulation is relatively small, so the main results will not quantitatively change under our current assumption on the demand shifter. The small amenity effect of regulation is due to the low correlation between our regulatory index (CALURI) and per capita income, as most of the sub-indices underlying CALURI is associated with the supply side. The only sub-index directly related to the demand-side effect is the open space index, which is binary in the survey with low factor weight in CALURI (13%). Our model assumes that amenities are incorporated in the city income. In the empirical model, we do control amenity variables including air quality, distance to the coast and distance to CBD.

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 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. 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.[14] The share of households located in city j is 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.

3.3 Housing Developer Profit Maximization

In each city, we assume there is a local housing developer who operates a Cobb-Douglas production technology using land L and non-land input N to make housing production. Both land and non-land input are immobile across cities. The housing developer pays a marginal housing supply cost c_j for each unit of land. The marginal cost c_j includes the construction cost of materials and labor c_0 which is 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.

$$\max_{\{L_j, N_j, H_j\}} p_j H_j - c_j L_j - r_j N_j \quad s.t.\ H(L,N) = A_0 (L^{\sigma} N^{1-\sigma})^{\varepsilon},\ c_j = \tau_j c_0 \tag{6}$$

where $A_0 > 0$ is the aggregate productivity, σ is the land input share, r_j is the price of the non-land input, and $\varepsilon < 1$ controls the curvature of the production technology.[15]

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

[15] We proceed with the assumption that the housing production function exhibits decreasing returns to scale for two reasons. First, the assumption provides a straightforward way to motivate an upward sloping housing supply curve and to relate regulation to the level of housing supply and housing price. In the appendix, we provide a micro foundation of the production technology which leads to the same supply curve. Second, the assumption captures the price elasticity of housing supply through a simple parameterization. We focus on the average price elasticity, because the effect of regulation on the growth of housing supply in response to housing price is mixed (Larson, Yezer and Zhao, 2018;

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 captures, for example, the time length of permit approval, the open space requirement etc. We interpret the regulation intensity τ_j as the aggregate of underlying regulatory factors, $\tau_j = \Pi_s(\tau_j^s)^{\rho_s}$, where τ_j^s is an underlying factor and $\rho_s > 0$ is the corresponding factor weight.[16] We assume the stock of non-land input is $N_j = 1$ in each city. Hence, the housing supply curve can be rewritten as follows:

$$H_j^S(p_j) = A_0^{\frac{1}{1-\theta}}\left(\frac{\theta p_j}{c_j}\right)^{\frac{\theta}{1-\theta}} \tag{7}$$

3.4 Equilibrium Conditions and Housing Prices

Two equilibrium conditions are necessary to solve 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 for prices simultaneously. The market clearing condition (8) requires that we equate housing demand by aggregating individual demand (2) to housing supply (7) within each city.

$$q_j(p)\int h_{ij}^D(p_j)di = H_j^S(p_j),\ \forall j \in S \tag{8}$$

The housing demand in city j is thus the product of the moving probability q_j and the expected individual demand in city j.[17] 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.

We proceed with the case where $n = 2$. That is, for an arbitrary city j, there is a single aggregated 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.[18] We solve for log housing prices $\ln(p_j)$ in closed form as follows.[19]

Broxterman and Liu, 2019). In the paper, we focus on the parameter $\theta = \sigma\varepsilon$ that is related to the price elasticity of housing supply $\theta/(1\text{-}\theta)$ and the land input share σ.

[16] We assume the relationship between the single measure and the underlying factors of regulation follows a product form. The log of τ_j corresponds to the predicted score regression in principal factor analysis that we use to construct a single index from multiple measures of land use regulation.

[17] As Y_i and Z_j are assumed independently distributed, we can integrate 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.

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

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

$$\ln p_j = [\theta \ln c_0 + \theta \ln \tau_j] - (1-\theta)\ln\left[1 + e^{(2\lambda-1)\phi(z_j - z_{-j}) + \frac{\theta}{1-\theta}\lambda(\ln\tau_j - \ln\tau_{-j})}\right] \\ +[(1-\theta)(\ln Y_0 + \phi z_j) - \ln A_0] + [(1-\theta)\ln\alpha - \theta\ln\theta] \quad (9)$$

The first two terms in the price equation are functions of regulation. The first term is the direct or partial equilibrium (PE) effect, which captures the impact of absolute level of home regulation on home prices. The second term is a nonlinear indirect or general equilibrium (GE) effect, which captures the impact of relative regulation of home and neighboring cities on home prices along with relative city income.[20] The price level in city *j* depends positively on regulation in the neighboring city, *i.e.* the outside moving option, all else equal.[21]

We first estimate this model with a linearly approximated GE effect and then consider non-linear approximations and model extensions, which are all accommodated in a general form of the following housing price equation:[22]

$$\ln p_j = \underbrace{F(\ln\tau_j, z_j)}_{PE\ Channel} - \underbrace{G(\ln\tau_j - \ln\tau_{-j}, z_j - z_{-j})}_{GE\ Channel} + \beta_0 \quad (10)$$

where β_0 is a term unrelated to regulation or income, with function *F* showing prices increasing in the levels of regulation and income (with regulatory impact also depending on income), and with function *G* showing prices increasing in relative regulation and relative income.

$$\frac{\widetilde{p}_{mt} - p_{mt}}{p_{mt}} \approx \ln(\widetilde{p}_{mt}) - \ln(p_{mt}) = \underbrace{(\widetilde{PE}_{mt} - PE_{mt})}_{PE\ Contribution} + \underbrace{(\widetilde{GE}_{mt} - GE_{mt})}_{GE\ Contribution} \quad (11)$$

4. Data

We require data on land use regulation, housing prices and characteristics, and local per capita income, as well as macro factors. Table 2 summarizes the spatial coverage of regulation and pricing data. Here we describe the main components of each dataset used in the estimation.[23]

[20] In the appendix, we extend the model to a political economy model with optimal regulation choices and discuss how a stronger GE effect measures the extent to which a local policy maker over-regulates a city, relative to a socially efficient level of regulation.

[21] Higher income in the neighboring city will increase the neighboring housing prices due to a rightward shift in the demand curve. Higher neighboring housing prices will trigger the spill-out of demand, thus a rightward shift in the demand curve at home. Our model thus predicts a positive impact of neighboring income on the home housing prices.

[22] The second term in equation (9) formalizes the spillover effect from Pollakowski and Wachter (1990), modeled as a consequence of household mobility. In the appendix, we show the details of linear and quadratic approximations.

[23] See the appendix for additional details on the data description, filtering and summary statistics.

4.1 Land Use Regulation Data

For land use regulation, we use the Wharton Residential Land Use Regulation Index (WRLURI) for California (Gyourko et al. 2008).[24] Figure 2 shows the spatial distribution index values across the 185 cities covered by the survey (out of 482 California cities). Figure 3 shows the location of cities in and out of the sample. WRLURI provides 11 sub-indices. We use the 8 sub-indices that have cross-city variation to construct a single regulatory measure for each locality, including the 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). We apply a principal factor analysis to these and define the predicted score of the first factor as our measure of regulation, as done in Gyourko et al. (2008). We derive and normalize the score standardized to zero mean and unit variance and define this as the California Land Use Regulation Index (CALURI). CALURI ranges from -3.23 to 3.38 for cities in California. One standard deviation (SD) increase in CALURI is proportional to one SD increase in all underlying sub-indices, with the marginal contribution proportional to the factor loading.[25] Local political pressure (which reflects the total degree of involvement by various local entities in the development process), local project approval (which counts the number of approvals needed for a project that does not need rezoning) and local zoning approval (which counts the number of approvals needed for a project that entails rezoning) are the leading factors contributing 21%, 21%, and 18% to the variation of CALURI.[26] [27] Table 2 reports summary statistics for CALURI and the 8 sub-indices.[28]

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[24] We focus on California, because the coverage of regulation and the housing data in California is much better than for other states and California cities appear to vary greatly in their degree of regulation (Fischel, 1995). The Wharton survey is a cross-sectional survey and WRLURI is estimated at the city level. The number of cities covered by the Wharton survey in California is one of the highest among all states. We report the response rate by MSA in California in the appendix.

[25] The model counterparts of regulation are $\ln(\tau_j)$ for CALURI and $\ln(\tau_j^s)$ for the sub-index s. We can recover the marginal contribution of the sub-indices by regressing CALURI on the standardized sub-indices without a constant. $CALURI_j = 0.418LPPI_j^{std} + 0.412LPAI_j^{std} + 0.351LZAI_j^{std} + 0.255OSI_j^{std} + 0.151EI_j^{std} + 0.147SRI_j^{std} + 0.133ADI_j^{std} + 0.118DRI_j^{std}$, where *std* means that a sub-index is normalized to zero mean and unit variance. The marginal contribution of the sub-indices can be mapped to the estimated parameters of $\{\rho_s\}$. Because CALURI is a predicted score, we have re-normalized CALURI to zero mean and unit variance after factor extraction. We show the density distribution of the 8 sub-indices in the appendix. 3 sub-indices are binary (density restriction, 6%; open space, 13%; exactions, 8%) and 1 sub-index is highly concentrated (supply restriction, 7%). The approval delay contributes 7% to CALURI.

[26] We use the aggregate index instead of the sub-indices in analysis, for similar reasons discussed in Glaeser and Ward (2009) and Hilber and Robert-Nicoud (2013). Compared to the individual sub-indices that are sparsely distributed (see the appendix for the distributions for each sub-index), CALURI provides a smooth and unimodal measure of regulation, making the estimation of a marginal effect of regulation possible.

[27] As political preference explains large variation of CALURI, we use the US election data to deal with the endogeneity concern of regulation and to derive the city-level voting share for the Republican party in the Presidential Election. The description of the election data and specifications with endogenous regulation are in the appendix.

[28] The indices are weighted by the number of property sales. CALURI has a positive weighted mean 0.27, a weighted median -0.01, and a weighted standard deviation 1.23. Because CALURI is normalized to zero mean and unit variance, the weighted statistics show concentration of sales in more regulated and more populated cities in our sample.

Because the Wharton Regulatory Index is only available for 2006, we also use the recently fielded Terner Center California land use survey (Mawhorter and Reid, 2018). To make our estimation results based on the Terner and Wharton surveys comparable, we construct another regulation index (TCLURI) using similar survey questions and index construction method from the Terner survey.[29] 252 out of 482 cities are covered by the Terner survey, with 102 of them overlapping with the California cities in the Wharton survey, with the correlation of CALURI and TCLURI in the overlapping cities equal to 0.43.

4.2 Housing and Regional Data

For housing data, we use Zillow Transaction and Assessment Dataset (ZTRAX), which provides transaction prices and housing characteristics from 1993 to 2017.[30] We include the following housing characteristics: transaction year, property use, number of bedrooms and bathrooms, property age, property size and distance to the Central Business District (CBD). We use the city name as the key to match transaction data to the regulation data. We include two additional regional controls: the number of days with good air quality by year and by MSA from the Environment Protection Agency and the distance from the centroid of a city to the Pacific coast.[31] In Table 3, we report the summary statistics for housing characteristics. The mean sales price adjusted for inflation is $370,000 in 2006 dollars. The average property size is 1,700 square feet. The average property age 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 CBD is 28 miles and 8 miles, respectively.[32] There are 4,620 county-city-year combinations for 1993-2017.[33]

[29] The Terner survey which builds on the Wharton survey and others is the most recent and focuses exclusively on jurisdictions in California. We group survey questions into different topics of regulation and construct sub-indices based on the survey answers. By selecting 8 topics that Mawhorter and Reid (2018) identify to be comparable or similar to those in the Wharton survey or that we think are relevant, we use the principal factor analysis to construct the Terner Center Land Use Regulation Index (TCLURI), similar to CALURI. The 8 sub-indices we construct are: Development Constraint Index, Project Approval Index, Approval Time Index, Zoning Restriction Index, Affordable Restriction Index, Approval Delay Index, Construction Limit Index, Local Opposition Index. The details of data description, index construction and estimation results comparing specifications with TCLURI and CALURI are reported in the appendix.

[30] More information on ZTRAX can be found at 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.

[31] Environment Protection Agency (EPA) classifies each day into one of the seven groups (Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, Hazardous). This measure is highly correlated with other air quality measures (the annual median or maximum Air Quality Index, days with NO_2, days with PM 2.5 etc).

[32] In the appendix, we report the property use distribution. 76% properties are single-family, followed by 21% of condos.

[33] Note that the county-city-year combinations will count a city spanning its jurisdiction in two neighboring counties as two separate cities in empirical analysis. On the other hand, not all cities are present in the whole sample period. For the cities on the county boundaries, we will assign the same city regulation to two city divisions. In estimation, we will weigh each division by the number of transactions in each cell indexed by county, city and year.

4.3 Income and Macroeconomic Data

4.3.1 Income data at the MSA level

Annual per capita income data at the MSA level is derived from the Moody's Analytics MSA dataset, based on BLS data. In the absence of annual city-level income data,[34] we match 179 out of 185 cities in the Wharton survey to an MSA in Moody's data, as shown in Table 4, The matched sample covers 25 out of 26 MSAs in California from 1993 to 2017 (with 5.3 million residential transactions in 39 out of 58 California counties). Figure 4 shows average housing prices and income for the 25 MSAs as of 2017. Figure 5 shows average housing prices and per capita income for the state and metros over time, adjusted for inflation. We collect additional regional demographic and voting data to deal with the potential endogeneity of income and regulation.[35]

4.3.2 Macroeconomic data

We use annual data and control for changing macroeconomic conditions over time. The data cover the boom and bust period in residential mortgage and housing prices from 2001 to 2007 in California. The time series variation of housing prices may depend heavily on credit conditions (Choi et al, 2016). We control for this by including two macro variables: the growth rate of household mortgages and the real 30-year fixed-rate mortgage rate, shown in Figure 6.[36]

4.3.3 Income Data for the Analysis of Greater Los Angeles

For the analysis of Greater Los Angeles (Los Angeles, Orange and Ventura counties), we require city-level per capita income to capture city-level cross-sectional variation of housing prices attributable to income differences. We derive this city-level per capita income (and other statistics) by aggregating

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[34] We use GMP and population from Moody's data to calculate per capita income. Moody's data at the MSA level traces back to 1990 and allow us to use observations from all sample years in ZTRAX. It aggregates statistics based on the 2013 OMB delineation of metro areas for comparison over time. Data description are available in the appendix.

[35] Besides its lag term as a natural instrumental variable of per capita income, we additionally include three demographic variables: the share of high education, the average population age, and the share of high-tech jobs. Data on the share of high education and the average age come from the American Community Survey (ACS) 1-year Micro data. The share of high education includes college and graduate education for at least one year. Data on the share of high-tech jobs are compiled by Moody's Analytics. The average share of high education is 36%, while 6.84% of the total employment are high-tech jobs. The average population age is 35 years. We show that the demographic variables are highly correlated with per capita income, and they pass the test of relevance assumption. The correlation of the per capita income with the share of high education, the population age, and the share of high-tech jobs to be 0.823, 0.753 and 0.651, respectively. Those instruments also pass the Sargan-Hansen's J test for exclusive restrictions. A similar set of demographic variables have been adopted in Ihlanfelt (2007) to justify instrument exogeneity in the price equation. The details on data description and test results are available in the appendix.

[36] 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. 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 (adjusted for inflation) comes from Primary Mortgage Market Survey by Freddie Mac.

census tract data and using tract population as the weight in the American Community Survey (ACS) 2016 5-year data.[37] Figure 7 show prices, per capita income, and CALURI for Greater Los Angeles.[38]

5. Estimation Results for California

We discuss the estimation methodology in Section 5.1 and results in Section 5.2. We discuss results for the decomposition of the direct (total) effect of regulation into partial and general equilibrium effects and simulate the impact of regulatory change, assuming the case of reducing regulation to that of the mean and least regulated locality in the MSA in Section 5.3

5.1 Estimation Method

To test the empirical model for California, we assume that the outside moving option of an arbitrary city *j*, called city *-j*, is interpreted as a city with average income and regulation, *i.e.* an area with average local characteristics. The assumption simplifies the regulatory index (CALURI$_{-j}$ = 0) and income (z_{-j} = E$_j$[z_j]) of city *-j*.[39] Besides the factors related to regulation and per capita income (f_1), we control the housing (f_2), regional (f_3) and macro characteristics (f_4) in the following empirical model.[40] [41]

$$
\begin{aligned}
&\ln p_{ijmt} = \beta_0 + f_1 + f_2 + f_3 + f_4 + \varepsilon_{ijmt}, \text{ where} \\
&\quad f_1 = \theta \cdot CALURI_j - \tfrac{1}{2}\theta\lambda \cdot (CALURI_j - CALURI_{-j}) \\
&\qquad + (1-\theta)(\tfrac{3}{2} - \lambda)\phi z_{mt} + \tfrac{1}{2}(1-\theta)(2\lambda - 1)\phi z_{0t} \\
&\quad f_2 = X_{ijmt}\gamma,\ f_3 = N_{jmt}\chi,\ f_4 = M_t \nu,\ z_{0t} = \textstyle\sum_m g_{mt} z_{mt},\ \sum_m g_{mt} = 1,\ \lambda = \frac{\alpha(1-\theta)}{\alpha(1-\theta)+1}
\end{aligned}
\tag{12}
$$

The log real housing price as the dependent variable has 4 subscripts: 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 mean of per capita income, weighted by the population share g_{mt} of MSA *m* in year

[37] The 5-year estimates rely on the 2012-2016 data but do not represent the statistics of any single year. Per capita income is a lagged variable based on the ACS 5-year estimate, so we treat it as exogenous in analyzing Greater Los Angeles.

[38] The heat maps of housing prices and per capita income for all cities in Greater Los Angeles, as well as the map of WRLURI for the cities covered by the Wharton survey are available in the appendix.

[39] An ideal case of defining neighboring regulatory index would be to use the regulatory information on the neighboring cities throughout California. 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 on no spatial information in estimation. We relax the assumption and work on a measure of city-specific neighboring index in the analysis of Greater Los Angeles.

[40] The structural equation looks similar to a reduced-form model. In the appendix, we show the marginal effects estimated from the reduced-form and the structural models are not significantly different, but interpretations of two models are different. The structural model can be interpreted as a constrained reduced-form model in which equilibrium conditions impose restrictions on the marginal effects. With the constraint on the structural model, we can decompose the regulatory effect into the PE and GE effects, separating the price impact due to the supply shift and the demand shift.

[41] We include the time dimension for a larger pooled sample, with more power to identify the parameters by reducing the standard errors and to produce more stable estimates by smoothing out the unobserved time-varying factors.

t. If only a cross-section of transactions is used for estimation, we lose the structural information in the marginal effect of z_{0t} which will be absorbed in the constant term. In f_2, we control housing characteristics X_{ijmt}.[42] In f_3, we include the number of days of good air quality in an MSA and the city distance to the Pacific coast as neighborhood controls N_{jmt}. In f_4, we control for macro conditions M_t, including real mortgage credit growth and real 30-year fixed rate mortgage rate.

To achieve identification of the model, we proceed in two steps. First, we separate the housing price variation associated with housing, regional and macro characteristics (f_2, f_3 and f_4) from the price variation associated with regulation and income (f_1), using a linear model.[43] Second, we use the residual of the housing price equation from step 1 to estimate the unknown parameters (θ, ϕ), imposing a parametric assumption of $\alpha = 0.2$.[44] We weight each county-city-year observation in step 2 by the number of sales in the county-city-year combinations from step 1, which captures the impact of population. Our estimation strategy is to use two-stage Generalized Method of Moments (GMM) to estimate the structural parameters (Hansen, 1982). We base the GMM estimation on three exclusion restrictions to achieve identification of (θ, ϕ): $CALURI_j$, z_{mt} and z_{0t} are orthogonal to the residual of the housing price equation in step 1 at the city level.

5.2 Estimation Results for California

Section 5.2.1 presents estimation results for parameters and marginal effects for a one standard deviation or a unit increase in regulation on housing prices with exogenous and endogenous income, as reported in Table 5a and 5b, respectively for 1997-2017 and for 2012-2017. We use local data on regulation (from the Wharton survey fielded in 2009) and annual MSA income data. We show comparative results using the Terner Center regulatory index (fielded in 2017) in Table 5c. We discuss how regulatory effects vary over time in Section 5.2.2, as shown in Figure 8. We test for whether regulation's impact varies with MSA income, in Section 5.2.3, as shown in Table 5d (5e) for 1997-2012 (2012-2017) and in Figure 9.

5.2.1 GMM Estimators

Model 1 in Table 5 is based on an assumption of exogenous per capita income. A one standard deviation increase or a unit increase in regulation (CALURI) increases housing prices by 2.7% for 1993-2017 and 6.0% for 2012-2017. A one percent increase in per capita income increases housing prices by 0.55%

[42] The housing characteristics include the property use, the number of bedrooms/bathrooms, the property age, the log property size, and the log miles to CBD. See appendix for details on how we code these variables

[43] The estimation results in step 1 is available in the appendix.

[44] We impose $\alpha = 0.2$, because estimating the housing consumption share is not the focus of our paper. The value α is based on the US real housing service and utilities expenditure in the real personal consumption expenditures from BEA.

(0.56%) for 1993-2017 (2012-2017).[45] The marginal effect of log mean income which measures the impact of neighboring income is negative as expected, -0.14% for 1993-2017 and -0.15% for 2012-2017, as home location choice depends positively on home income and negatively on neighboring income (This is as expected: higher neighboring income results in lower home housing demand, thus lower home housing prices). The parameter estimates for income elasticity of demand and price elasticity of supply, shown in Table 5, are similar to those in the literature and hold across all models.[46] Parameters and marginal effects are all statistically significant at a 1% level, as shown in Table 5.

Because per capita income may be endogenous, we modify Model 1 and include in Model 2 the lag terms of the log per capita income ($z_{m,t-1}$) and the mean of log per capita income ($z_{0,t-1}$) to instrument their contemporaneous counterparts. We show the estimates of Model 1 and Model 2 are not qualitatively different. In Model 3, we build on Model 2, and add demographic variables (share of high education, population age, and share of high-tech jobs) as instruments for per capita income in addition to lagged terms. Results remain qualitatively similar. In Model 3, one SD increase in CALURI increases housing prices by 3.3% (6.2%) for 1993-2017 (2012-2017), while a 1% increase in per capita income increases housing prices by 0.51% (0.57%) for 1993-2017 (2012-2017).[47] [48]

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[45] The marginal effect is based on California instead of the US average as the reference point. California is more than 0.5 SD higher in terms of WRLURI than the average regulation in the US (Table 3). In the appendix, we replicate the benchmark estimations but instead use WRLURI as the regulatory measure, leading to larger estimates of marginal effects.

We show in the appendix that housing characteristic controls are essential for estimation of the parameters. The income elasticity in the specification without housing controls is more than 0.8, double the estimate in the literature.

[46] The estimate of the income elasticity of demand ϕ for 1993-2017 and 2012-2017 are 0.43 and 0.46 respectively, consistent with the estimates in the literature (Hansen et al, 1996; Zabel, 2004; Rosenthal, 2014). Hansen et al (1996) find that the income elasticity of demand for owners is increasing in the permanent income, ranging from 0.08 at 10th percentile of the income distribution to 0.80 at the 90th percentile. Zabel (2004) find similarly that the income elasticity of housing service is increasing in income and ranges from 0.16 at 10th percentile of income distribution to 0.64 at 90th percentile. Rosenthal (2014) uses AHS (1985-2009) and finds the income elasticity is 0.13 for renters and 0.40 for owners.

The estimate of the price elasticity of supply $\theta/(1-\theta)$ for 1993-2017 and 2012-2017 are 0.03 and 0.07 respectively, consistent with the estimate by Trulia (2016). Trulia (2016) finds that the long-run housing supply elasticity (1996-2016) in California ranges from 0.04 to 0.11 (0.21 to 0.26) for the coastal (inland) metros. Quigley and Raphael (2005) examine the relationship between housing stock and price change in California using 1990 and 2000 Census data. They find price elasticity of housing supply ranges from -0.036 to 0.358 for multi-family and from -0.203 to 0.074 for single-family housing. The elasticities are weakly significant with 90% confidence. Mayer and Somerville (2000) distinguish the housing supply and housing start elasticities. They also find a relatively small price elasticity of supply of 0.08 in the US from 1975 to 1994.

[47] In the appendix, we test the validity of the instruments used in all models in Table 5 and show in the appendix that they all pass the Sargan-Hansen's J test of exclusive restrictions. We also show that the current per capita income is highly correlated with the instruments which pass the regression test of the relevance assumption.

[48] In the appendix, we also consider specifications with endogenous regulation using political preference (log odds ratio of the voting share for the Republican party in the Presidential Election) as the instrument. We do not find the estimated parameters are much different by endogenizing regulation. In addition, the concern of endogenous regulation is limited, as we find the p-values of the Sargan-Hansen's J tests for Table 5 (in the appendix) doesn't reject instrument validity.

We re-estimate Model 3 using Terner Center survey data for the 2012-2017 sample.[49] We find that the marginal effects of regulation and of per capita income on log prices, estimated with the Terner survey, are not statistically different from the marginal effects estimated with the Wharton survey for this period, as shown in Table 5c.

We compare estimated effects to those in the literature in Table 6. As noted, Jackson (2018) uses a 2017 land use survey of California cities, pooling city prices in 2000, 2006 and 2012, and finds a 5% regulatory effect on housing prices for a one SD change in the index (Table 6a). Our estimates of the marginal effects of regulation (3.31% for 1993-2017; 6.19% for 2012-2017) in California bound Jackson's estimated effect. We describe how our results compare to those for San Francisco (Quigley et al. 2008) below.

5.2.2 Time-varying Regulatory Effects

We explore parameter shifts over time in more detail by estimating the specification with a 3-year moving bandwidth. The choice of the bandwidth balances the tradeoff between examining the time-varying regulatory impact and gaining more statistical power to identify parameters.[50] In Figure 8, we show that the estimated regulatory impact increases over the time period 1993 to 2017. The estimated marginal effect of regulation increases from 2.5% in early 2000, to 5% in 2006-2008 and to 8% in 2015-2017.[51]

The upward trend of the regulatory effect may be driven by increased stringency of regulation, which is not testable based on one wave of the regulation survey.[52] On the other hand, the upward trend

[49] Columns 1 and 2 of Table 5c use a subset of overlapping cities covered by both surveys, while Columns 3 and 4 use all cities covered by the Terner and the Wharton surveys respectively. In Columns 1 and 2, the number of cities in both surveys (102) is less than 60% of the number of cities responding to either of the survey. We see a larger marginal effect of regulation and a smaller marginal effect of per capita income in the Wharton survey than in the Terner survey. If we use all city samples in both survey and do the comparison, we find that the marginal effects of regulation and of per capita income are not statistically different in Columns 3 and 4.

[50] The latter concern is related to the identical outside moving option that assumes away cross-sectional variation of neighboring income (z_{0t}) whose effect will be absorbed in the constant term in a cross-sectional model. We thus adjust our estimation strategy to additionally explore the time-series variation of housing prices to gain more statistical power and achieve better fit of the model.

[51] Estimations with a shorter horizon lead to lower statistical power and a wider confidence interval. For years before 2006, the estimated marginal effects over time are weakly significant at the 10% level, while the marginal effects estimated for more recent years are significant at the 5% level.

[52] In the appendix, we use the Wharton survey (2006) and the Terner survey (2017) to consider how regulation may have changed over time. Instead of looking at the average regulatory impact in California (which is survey specific), we examine how the relative difference of the regulatory impacts in southern and northern California changes over time, relative to the California mean over time. The upward trend of regulatory impact for California (Figure 8) is associated with an increasing regulatory impact in southern California (4.3% to 7.2%, closer to the regulatory impact in northern California which is relatively unchanged: 7.2% to 6.7%). This may be due to a relatively greater increase in regulation in the same localities or to an increase in regulation that are not covered by the Wharton survey. However preliminary results from a re-fielding of the Wharton survey (as described in the following footnote) show no evidence of an increase

may be driven by an increase in otherwise unmeasured factors associated with the index, such as a declining spillover effect, which could be associated with an increased spatial coverage of regulation for newly incorporated municipalities without an increase in the average regulatory index for existing municipalities.[53]

5.2.3 Spatial Heterogeneity of Regulatory Effects by MSA Income across California

We expand Model 3 with interactive and the quadratic effects on income in Model 4 to test for how regulatory effects on house prices vary by level of MSA income and by MSA (as shown in the following section).[54] We make a parametric assumption to restrict attention to the class of models that nests Model 3, so that we can test whether the marginal effects are constant as the null hypothesis in the extended housing price equation.[55]

$$\begin{aligned} \ln p_{ijmt} &= \beta_0 + f_1 + f_2 + f_3 + f_4 + \varepsilon_{ijmt} \\ \text{where } f_1 &= \theta\delta_0 \cdot CALURI_j - \tfrac{1}{2}\theta\lambda \cdot (CALURI_j - CALURI_{-j}) + \theta\delta_1 z_{mt} \cdot CALURI_j \\ &\quad + (\tfrac{3}{2} - \lambda)(1-\theta)(\phi_1 z_{mt} + \phi_2 z_{mt}^2) + (\lambda - \tfrac{1}{2})(1-\theta)(\phi_1 z_{0t} + \phi_2 z_{0t}^2) \\ f_2 &= X_{ijmt}\gamma,\ f_3 = N_{jmt}\chi,\ f_4 = M_t \nu \end{aligned} \tag{13}$$

As seen in Table 5d (Table 5e) for 1993-2017 (2012-2017), individual tests of the interactive and quadratic effects to be zero are rejected at 1% level, and we jointly test the hypothesis of $\delta_0 = 1$, $\delta_1 = 0$, $\phi_0 = 0$ and $\phi_2 = 0$ using a Wald test and reject it at 1% level. Hence, there is evidence for a heterogeneous impact of regulation by level of per capita income. While the linear approximation is sufficient to examine the average marginal effect, it is not sufficient for the measurement of the effect of regulation at different MSA income levels. The historical (recent) estimates of the marginal effect of regulation at the mean of the log per capita income is 2.83% (5.64%), as noted. For an MSA with one SD above the mean per capita income, one SD increase in regulation based on historical estimates (1993-2017) is

in measured regulatory stringency for the same localities for which data are available in both periods, suggestive of an increase in regulation in surrounding cities.

[53] Gyourko and Krimmel (2019) find that measured regulation is persistent from 2006 to 2018 nationwide, suggesting that the upward trend of the regulatory effect might be associated with the latter possibility. Comparing the 2006 and 2018 waves of the Wharton survey, Gyourko and Krimmel (2019) find no evidence that the distributional pattern of regulation in 2006 and 2018 are significantly different.

[54] We extend the marginal supply cost and the demand shifter to take the following forms: $c_j = \tau_j^{\delta_1 z_j + \delta_0} c_0$ and $A_j = e^{\phi_0} Z^{\phi_2 z_j + \phi_1 - 1}$ with the details of extension available in the appendix. The first extension which introduces an interactive term of regulation and income implies that the regulatory effect may depend on per capita income which reflects land productivity. Tighter regulation in a more productive higher income city is likely to have a stronger regulatory impact on housing prices than in a lower income city, where the demand for land will be less. The second extension which introduces a quadratic term on income implies that households in richer communities may show a stronger response of housing demand to income at higher levels of income.

[55] We assume that $\delta_1 E(z_{0t}) + \delta_0 = 1$. 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.

associated with 5.02% increase in housing prices and with an 8.42% increase using 2012 to 2017 data.[56] Figures 9a and 9b show a flat price surface based on Model 3 and a convex price surface based on Model 4 respectively as a function of CALURI and per capita income. The comparison visually shows the degree to which regulatory impact increases in income for localities away from the mean.

Model 4 introduces interactive and quadratic effects of per capita income to allow the marginal effect of regulation to depend on income, but is restricted to linear impacts of relative regulation and relative income. Model 5 extends Model 4 to allow for non-linear impacts of relative regulation and relative income.[57] In the next section, we use Models 3-5 to estimate the partial and general equilibrium effects by MSA using the California sample.

5.3 Decomposing the Total Regulatory Effect into Partial and General Equilibrium Effects

For California, we consider one SD increase in home regulation and decompose the total effect of one SD increase in regulation on housing prices into a partial equilibrium effect (PE) and a general equilibrium effect (GE). For the individual MSAs, we evaluate the total, PE and GE effects at the regulation and per capita income of the MSA.[58] We also simulate the impact of a change in regulation for selected localities within MSAs to that of the mean and least regulated locality within the MSA to illustrate the degree of variation in local stringency of regulation.

As previously discussed, in the general form of the decomposition in equation (10), we define the PE effect as the housing price impact of home regulation that affects the cost of local housing supply, and the GE effect as the price impact of relative regulation and relative income that determine the moving probabilities (the decomposition is additive so that the total effect of regulation is the sum of the PE and GE effects).

In Table 7, we report four sets of decomposed effects for 2012-2017. The first and second sets of decomposition (Columns 1-3 and 4-6 respectively) are based on the estimated parameters from Models 3 and 4 respectively. Model 3 assumes zero interactive and quadratic effects of the regulation and income levels and is nested in Model 4 that allows non-zero interactive and quadratic effects. Both Models 3 and 4 are restricted to linear impacts of relative income and relative regulation. The third set of decomposition (Columns 7-9) based on Model 5 allows non-linear impacts of relative income and

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56 We show in the parameter estimates of Model 4 that the income elasticity of housing demand, $2\phi_2 z_{mt} + \phi_1$, is increasing in per capita income, consistent with the finding in Zabel (2004).

57 By quadratically approximating the log moving probability, Model 5 that extends Model 4 includes an additional factor f_5 in equation (13) with the interactive and quadratic terms of the demeaned regulation and demeaned per capita income to allow the general equilibrium effect to correlate with regulation and income (see appendix for the extended housing price equation).The average marginal effects are quantitatively similar in Models 4 and 5. Individual terms in Model 5 show less statistical significance than those in Model 4, because those terms are correlated.

58 We summarize here how we define the PE and GE channels, with additional discussion of PE-GE decomposition in the appendix.

relative regulation, extending the GE effect from being a constant to correlate with regulation and income. The fourth set of decomposition results (Columns 10-12) based on Model 5 relaxes the assumption of constant neighboring regulation by directly including the average MSA regulation ($CALURI_{-j}$ in equation (13)) in the estimation. We add these additional sets of decomposition to test for robustness of results under different assumptions.

Based on Model 3, Columns 1-3 in Table 7 show that a 6.19% total effect of regulation in California for 2012-2017 is decomposed into a 6.72% PE effect and a -0.53% GE effect, while for 1993-2017, a 3.31% total effect of regulation is decomposed into a 3.60% PE effect and a -0.29% GE effect.[59] The relative impact of spillovers decreases somewhat which contributes to the increasing total effect, although as noted above, increases in the extensiveness of regulation cannot be measured, consequently, measured impact would be included in a larger PE effect.

Compared to Columns 1-3 with constant PE and total effects, across MSAs, Columns 4-6 using Model 4 with a linear approximation of the log moving probability as a function of relative income and relative regulation show that the PE effect is increasing in per capita income, and the GE effect is constant (-0.57%).[60] Columns 7-9 are based on Model 5 with a quadratic approximation of the log moving probability. Columns 10-12 additionally include metro-specific neighboring regulation in the measure of relative regulation.[61]

We report the size of the effects of increasing regulation by one standard deviation by MSA in Table 7. We apply the MSA average price response to a one SD increase in regulation in Table 7 to estimate the size of the regulatory impact in the largest California cites. San Jose and San Francisco MSAs are the metros with the highest estimated total effects of regulation on housing prices. The total effects of regulation in the San Francisco MSA estimated at 3.8% for 1993-2017 (see Column 9) is similar to the estimated effect found in Quigley, Raphael and Rosenthal (2008) of 3.8% to 5.3%, as shown in Table 6b.[62] Using 2012-2017 estimates (Columns 7-9), if home regulation increases by one

[59] The decomposition for 1993-2017 is available in the appendix. The linear approximation is sufficient to examine the average marginal effect. We show in the appendix that high order terms do not improve the estimate of the average marginal effect by comparing the linear to quadratic specifications of the log moving probability. The specification with quadratic approximation additionally includes the squared deviations from the mean of per capita income and regulation, and an interactive term of demeaned income and demeaned regulation. The functional form of the 2nd order approximated log price equation is available in the appendix. We find that the average marginal effects in the two specifications are not statistically different.

[60] Using the linear specification to infer the marginal effects is more accurate near the mean than away from the mean characteristics. Linearly extrapolated marginal effects for MSAs at tails of the per capita income distribution may have larger standard errors.

[61] In the appendix, we test for whether the estimation results of Models 1 to 5 for 1993-2017 (2012-2017) are robust to the assumption of identical outside moving option by directly controlling the MSA average regulation to measure the outside regulation of a city in equation (13). We report quantitatively similar results which are not driven by the assumption of constant neighboring regulation in the estimation of Models 1-5 and in the PE-GE decomposition.

[62] The decomposition for 1993-2017 by MSA is available in the appendix. For San Jose MSA, our estimated total effect for 1993-2017 is 3.80%. The local survey conducted by Quigley et al (2008) is based on the questionnaires of Gyourko

standard deviation (SD), the total effect on home prices is 7.71% (7.02%) for San Jose (San Francisco) metro area, equal to the home PE regulatory effect 8.06% (7.44%) mitigated by the housing demand spill-out of -0.35% (-0.42%). Table 7 shows a somewhat lower total effect of increasing regulation by one SD for Los Angeles MSA of 6.5% (PE = 6.97%, GE = -0.47%) and for San Diego MSA of 6.27% (PE = 6.76%, GE = -0.49%).[63] [64]

Given the range of regulatory levels in the MSAs, we can simulate the impact of regulatory change, of reducing the regulation in a highly impacted cities to its MSA mean or minimum levels to show how regulatory stringency varies across localities. In Table 8, we can simulate the impact of regulatory change, assuming the case of reducing regulation to that of the mean and least regulated locality in the MSA (based on recent estimates, 2012-2017) (As noted above, CALURI ranges from -3.23 to 3.38 across cities). If Los Angeles (LA) City (3.38) were to relax its regulation to the MSA mean level (-0.20), housing prices would be estimated to be 23% lower, attributed to 25% through the PE channel, with a -2% offset through the GE channel. If San Francisco City (1.04) were to relax its regulation to the MSA mean level (-0.22), housing prices would be estimated to be 8.83% lower, attributed to 9.36% through the PE channel, with a -0.53% offset through the GE channel. If San Diego City (0.30) were to relax its regulation to the MSA mean level (-0.25), housing prices would be estimated to be 3.49% lower, attributed to 3.76% through the PE channel, with a -0.27% offset through the GE channel. The GE effects are measured, assuming an average alternative regulation measure for all of California, without taking account of the spatial distribution of regulation, to which we now turn.

6. Estimation Results for Greater LA

Here, we model the local GE effect directly with spatial detail for the Greater Los Angeles area, which includes three counties (Los Angeles, Orange and Ventura) and 55 cities with survey responses (out of

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et al (2008) but is adapted to California. There are 65 and 17 cities in San Francisco and San Jose MSAs respectively (see the appendix for the city distribution by CBSA and Wharton survey coverage).

[63] For 1993-2017, total effects for Los Angeles and San Diego MSAs for 1993-2017 are 3.35% and 3.22% respectively, similarly lower than the total effects for 2012-2017. Given that San Francisco and San Jose MSAs have higher income (Figure 4), the correlation of regulatory impact and income is consistent with households in high-income areas being less willing to substitute higher income for a lower cost of housing.

[64] In the appendix, we report the estimated PE, GE and total effects over time based on a 3-year moving bandwidth, as shown in Figure 8. Besides the upward trend of the total effect over time, we in addition show in Figure 8 the GE-to-PE ratio in absolute value as a measure of relative share of price response attenuated by the spillover effect becomes smaller, going from 0.083 in 1995-1997 to 0.077 in 2015-2017. This suggests that households are less willing to move out of places with tighter regulation for lower housing cost and spatial substitutability is decreasing over time. To gain enough statistical power in estimation, we use Model 3 in Table 5 with a 3-year moving bandwidth to infer the time-trend of the average PE and GE effects, while we use Model 4 in Table 5 for historical (1993-2017) and recent (2012-2017) estimates of the PE and GE effects by MSA.

132), the highest response rate for a major metro.[65] This enables spatial analysis of price outcomes as related to local regulation and surrounding regulation, allowing us to examine intra-metro regulatory spillover effects on local housing prices. As noted, we use city- instead of MSA-level income to capture cross-sectional variation of housing prices attributable to income variation.[66]

6.1 Construction of Relative Regulatory Restrictiveness

In the reduced-form analysis of Greater Los Angeles, we can now identify PE and GE effects through an index of relative regulatory restrictiveness. Using the linear term on relative regulation to measure the GE channel in equation (13), we measure the relative restrictiveness index (RRI) as the difference between neighboring CALURI_{-j} and home regulatory indices CALURI_j.[67]

$$RRI_j = CALURI_{-j} - CALURI_j$$
$$\text{where } CALURI_{-j} = \sum_{k \neq j} weight_{jk} \cdot CALURI_k,\; weight_{jk} \propto z_j z_k / d_{jk}^2 \tag{14}$$

We construct CALURI_{-j} as a weighted average of the neighboring regulatory indices, with the weight depending on the city proximities. The weighting measure takes a gravitational form and puts more weight on the regulatory indices of nearby or high-income cities than remote or low-income cities.[68]

6.2 Estimation Results for Greater Los Angeles

We use Model 3 in Table 5 as our benchmark model.[69] We deal potential endogeneity of regulation and evaluate heterogeneous impacts of regulation by level of per capita income. For brevity, we report only the marginal effects of CALURI and RRI in the log price equation and contrast the specifications with and without RRI (full results are available in the appendix).

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[65] The city response rate in the three selected counties combined is 42% (55/132) and is the highest for California metros with sufficiently many cities. 30% (55/185) of the California cities in the Wharton survey are in Greater Los Angeles.

[66] This comes at the expense of losing time-series variation of income: the five-year ACS from which we get city income data collapses the time dimension for higher spatial precision in income estimates. This enables us to explicitly control for the relative regulatory restrictiveness which is founded on our spatial model but is not feasible to construct in the structural estimation.

[67] Compared with the definition of the GE effect in equation (10), equation (14) indicates RRI is equal to the linear part associated with relative regulation in the GE channel, assuming zero impact of relative income. We define RRI in this way to be consistent with the definition of relative regulatory restrictiveness in Pollakowski and Wachter (1990) who originate the discussion of the regulatory spillover effect. Moreover, in reduced-form analysis without parametric restrictions, we cannot discipline the relationship between relative regulation and relative income if both are included in RRI.

[68] The weight $weight_{jk}$ is interpreted as the outside moving probability from city j to city k. Equation (14) nests the case of identical outside moving option as a special case in the structural estimations (RRI_j = -CALURI_j). Alternatively, we consider the inverse of the squared distance as the weight on the neighboring cities and find that the estimated impact of RRI is quite similar. We will focus on the specifications under the gravity weight.

[69] We report the average marginal regulatory effects based on Model 3. In other model specifications that include interactive and high order effects, average marginal effects are found similar.

6.2.1 The Impact of Regulation

Columns 1 and 2 in Table 9 assume exogenous regulation, while Columns 3 and 4 endogenize regulation, with Columns 2 and 4 including RRI (with CALURI and RRI both endogenized in Column 4 using the home and the neighboring log odds ratios of the voting share for Republicans as the instrument). We estimate the marginal impacts of the home and the neighboring regulatory indexes and then derive the marginal impacts of CALURI and RRI.[70]

Under the assumption of exogenous regulation, Column1 estimates a 6.7% total effect of regulation, comparable to the structurally estimated total impact for the Los Angeles MSA of 6.5% (in Table 7 for the 2012-2017 sample). With RRI introduced, Model 2 reports the home regulatory effect (PE effect) and spillover effect (negative GE effect) to be 16.2% and 9.6% respectively. When we control for intra-metro variation of regulation and city income, we find far larger spillovers and estimate far larger partial equilibrium effects.[71]

Under the assumption of endogenous regulation, Column 3 in Table 9 reports an estimate of an 11.1% total effect of regulation, higher than the estimated impact of 6.7% under the assumption of exogenous regulation. The finding of an upward adjustment of regulatory impact after endogenizing regulation is consistent with Quigley et al (2008) and Ihlanfeldt (2007). When CALURI and RRI are both controlled and endogenized in Column 4, we find the home regulatory effect (PE effect) and the spillover effect (negative GE effect) to be 19.2% and 8.3% respectively. As Columns 1 and 3 are restricted specifications of Columns 2 and 4 respectively, the significant marginal effects of RRI show supportive evidence for the existence of regulatory spillover across jurisdictions.

6.2.2 Heterogeneous Impact of Regulation by City Characteristic

Columns 5 and 6 in Table 9 report results for the estimation of how the impact of regulation on housing prices depends on the neighboring locality regulation. We divide 55 cities covered by the Wharton

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[70] Using the log odds ratio instead of the voting share yields a domain on the real line. The dominant political impact in the factor loading of CALURI motivates us to use political preference to endogenize regulation. We aggregate the precinct-level data from the Harvard Election Data Archive to use the log odds ratio of the city-level voting share for the Republican party in 2004 Presidential Election as the instrument of regulation, so both CALURI and its instrument have the same domain on the real line. Quigley et al (2008) similarly use political preference to endogenize regulation in study of the San Francisco Bay Area. We follow the majority of the literature by assuming exogenous regulation from here on.

[71] For a robustness check, we compare the reduced-form results for Greater Los Angeles based on the Terner and the Wharton surveys. We confirm the previous finding that ignoring the regulatory surrounding by excluding RRI will underestimate the home regulatory effect. We find that both the home regulatory effect and the spillover effect based on the Terner survey are smaller than the estimated effects based on the Wharton survey, while the estimated total effects are comparable based on the subsample of overlapping cities. We think the difference may come from the different city coverage in two surveys, as the set of overlapping cities is small in Greater Los Angeles.

We replicate Columns 1 and 2 of Table 9 for 27 overlapping cities and 72 cities covered by the Terner survey. There are 55 cities covered by the Wharton survey and 132 cities in Greater Los Angeles. The comparison of the estimation results based on the Wharton and Terner surveys is available in the appendix.

survey in Greater Los Angeles into two groups, with high and low neighboring regulations, using the 75th percentile of the distribution of the neighboring regulations as the threshold (close to the mean level of regulation).[72] Building on Columns 1 and 2, we show how regulatory impact interacts with the surrounding regulatory regimes by including in Columns 5 and 6: an indicator of high neighboring regulation and an interactive term of the indicator and CALURI. In Column 5 without RRI controlled, we find that the interactive term is significantly positive (0.07), which indicates that the regulatory effect in localities surrounded by high regulation cities is larger.[73]

Besides regulatory surroundings, we examine how home regulatory and spillover effects vary across cities that differ in per capita income by dividing the cities in the Los Angeles MSAs into above- and below-median city groups by income. Columns 1-4 in Table 10 report the estimation results with four specifications: whether the city group is above or below the median and whether RRI is controlled. High-income cities have a larger total effect of regulation on housing prices than low-income cities (3.95% vs 1.54% for high- vs low-income cities). With RRI included, the coefficients of CALURI do not significantly differ by income grouping (at 14.1% for high and 15% for low) with the coefficient of RRI is larger for low-income cities (13.3% v. 10.5%), consistent with the results for the structural estimation of smaller spillover (a smaller GE effect in absolute value) for higher income cities.[74]

7. Discussion

We find empirical support for a price impact of local regulation that goes beyond the home jurisdiction. Our results based on structural and reduced-form estimations are closely connected, and they examine the price impacts of regulation from different but not inconsistent angles, under different underlying assumptions and granularity in the data. In the structural estimation for California, we find a total regulatory effect of 6.5% for the Los Angeles MSA, which is decomposed into a PE effect of 6.97% and a GE effect of -0.47%. In the reduced-form estimation for Greater Los Angeles (LA) where we have the city coverage to allow us to construct a direct measure of relative regulatory restrictiveness, we find a total regulatory effect of 6.7% (similar to the estimate from the structural model), a home regulatory effect of 16.2% and a spillover effect (negative GE effect) of 9.6%. With per capita income varying at the city level and the focus on cities only in Greater LA, we assume no inter-metro regulatory spillover

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[72] The 75th percentile of the neighboring regulation is about -0.04, close to zero, the average regulation in California. The division of transactions into two groups is more balanced under the threshold than under the mean or median.

[73] In Column 6 with RRI controlled, the coefficient on the interactive term is 0.07. The coefficient on RRI which measures the gap between neighboring and home regulations is not significant, because the indicator is highly correlated with RRI.

[74] In Columns 5 and 6, we test the difference of coefficients on CALURI and RRI between low- and high-income groups. we pool sales from two groups and include an indicator of high city income and an interactive term of CALURI (or RRI) and the indicator. We show in Columns 5 and 6 that the coefficients on CALURI are not significantly different and the coefficient on RRI is smaller for high income group.

out of Greater LA in the reduced-form analysis but are able to capture intra-metro spillover which is infeasible in our structural estimation. Both the structural and reduced-form results suggest that ignoring regulatory spillover will underestimate the local regulation, if similar regulation were implemented in surrounding localities, on local home housing prices, with intra-metro spillover far stronger than inter-metro spillover.[75]

Models ignoring regulatory surroundings mix the home regulatory and spillover effects in a unidimensional estimated effect. When we evaluate the regulatory impact of tightening regulation of a city by the same amount in Greater LA, the average regulatory impact is 6.7%. However, if regulation increased the same amount across all cities the impact would be 16.2%. The difference comes from ignoring regulatory surroundings by assuming away inter-connectedness of cities and treating LA cities as independent housing markets. We provide empirical support for the intuitive concept that when regulatory change is implemented more widely in closely connected housing markets, or over a larger region, the average regulatory impact on housing prices is larger. Recently the state of California has implemented an initiative to allow accessory housing and effectively decrease regulation across localities. Including general equilibrium effects points to the importance of how pervasively localities implement this deregulatory initiative for local house price outcomes.[76]

8. Conclusion

In this paper, we develop a general equilibrium framework to estimate the impact of local regulation on housing prices, including both direct effects, estimated in the literature, and spillover effects that mitigate direct effects. We use house transaction prices and characteristics over the years 1993 to 2017 with data on macro credit supply and regional per capita income together with the Wharton Residential Land Use Survey to structurally identify the impacts of land use regulation on housing prices.

We identify separate channels through which land use regulation can impact housing prices. Specifically, we characterize a partial equilibrium channel through which land use regulation increases the cost of local housing production in the home locality. In addition, we show a general equilibrium spillover effect in which demand shifts to other localities, with unchanged regulation. The measured effect of empirical studies that shows the impact of local regulation on local housing prices combines those two effects. The direct effect of regulation on housing prices, if implemented more widely, is

[75] That regulatory spillover is stronger within than between metros is consistent with the fact that within-county migration rate is more than 3 times higher than the inter-county or the inter-state migration rate (Molloy et al, 2011; Molloy et al, 2014).

[76] See *LA Times* (How lawmakers are upending the California lifestyle to fight a housing shortage): https://www.latimes.com/california/story/2019-10-10/california-single-family-zoning-casitas-granny-flats-adus

underestimated in the absence of allowing for a general equilibrium effect to capture the extent to which local regulation increases the demand for housing elsewhere.

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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)	366 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).
Albouy and Ehrlich (2018)	230 metros in US	Structural, OLS, IV	WRLURI	Housing price from 1% ACS sample with housing characteristics	2005-2010	1 SD increase leads to 6.5%-8.8% increase in price.

Note: for research on land use regulation and housing prices before 2005, see the summary by Quigley and Rosenthal (2005).

Table 2. 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	2.00	0.61	1.00	2.00
LPAI	1.69	1.00	0.98	1.00	2.00
DRI	0.15	0.00	0.35	0.00	0.00
OSI	0.87	1.00	0.33	1.00	1.00
EI	0.93	1.00	0.26	1.00	1.00
SRI	0.19	0.00	0.77	0.00	0.00
ADI	9.04	8.06	4.51	5.67	12.13
CALURI	0.27	-0.01	1.23	-0.41	0.60
WRLURI	0.80	0.55	0.79	0.16	1.50

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 3. 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
Property Age	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 CBD	28.08	8.14	240.19	4.44	14.5
Out of 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
Property Age	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 CBD	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.

Table 4. Sample Coverage by Area

	City	County	CBSA	Count
Land Use Sample	179	39	25	5,318,379
ZTRAX Sample	1,311	56	35	12,860,089

Note: *City* in the ZTRAX sample include cities, towns and Census-designated places, while the jurisdictions covered by the Wharton survey are the subset of 482 incorporated cities and towns in California. The sample covers the transactions from 1993 to 2017.

Table 5a. Benchmark Estimation: Parameters and Marginal Effects (1993-2017)

Parameter	Model 1	Model 2	Model 3
θ	0.0293***	0.0291***	0.0360***
	(0.009)	(0.009)	(0.009)
ϕ	0.429***	0.421***	0.396***
	(0.027)	(0.026)	(0.026)
Marginal Effect	Model 1	Model 2	Model 3
CALURI	0.0269***	0.0267***	0.0331***
	(0.008)	(0.008)	(0.008)
Log Income Per Capita	0.557***	0.547***	0.511***
	(0.034)	(0.033)	(0.033)
Avg. Log Income Per Capita	-0.140***	-0.138***	-0.129***
	(0.009)	(0.008)	(0.008)
Endogenize	No	Income (1)	Income (4)
Instrument	NA	Lag	Lag & Demo
N	4,620	4,620	4,620

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. A linear model is used to separate housing price variations due to housing, regional and macro controls in step 1, while GMM is used to estimate the model parameters in step 2. The estimation in step 1 is based on housing transactions from 1993 to 2017 in California. The controls used in step 1 include 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 days with good air quality. *Endogenize* indicates whether income or regulation is treated as endogenous. The number of instruments is listed in the parenthesis. The instruments used to endogenize a variable are listed under *Instrument*. *Demo* includes the share of high education, the population age, and the share of high-tech jobs.

Table 5b. Benchmark Estimation: Parameters and Marginal Effects (2012-2017)

Parameter	Model 1	Model 2	Model 3
θ	0.0654***	0.0654***	0.0672***
	(0.010)	(0.010)	(0.009)
ϕ	0.456***	0.444***	0.457***
	(0.043)	(0.043)	(0.041)
Marginal Effect	Model 1	Model 2	Model 3
CALURI	0.0602***	0.0603***	0.0619***
	(0.009)	(0.009)	(0.008)
Log Income Per Capita	0.572***	0.557***	0.573***
	(0.055)	(0.055)	(0.052)
Avg. Log Income Per Capita	-0.146***	-0.142***	-0.146***
	(0.014)	(0.014)	(0.013)
Endogenize	No	Income (1)	Income (4)
Instrument	NA	Lag	Lag & Demo
N	1,144	1,144	1,144

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. A linear model is used to separate housing price variations due to housing, regional and macro controls in step 1, while GMM is used to estimate the model parameters in step 2. The estimation in step 1 is based on housing transactions from 2012 to 2017 in California. The controls used in step 1 include 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 days with good air quality. *Endogenize* indicates whether income or regulation is treated as endogenous. The number of instruments is listed in the parenthesis. The instruments used to endogenize a variable are listed under *Instrument*. *Demo* includes the share of high education, the population age, and the share of high-tech jobs.

Table 5c. Comparison of the Estimated Results for California: Terner vs Wharton Surveys

Parameter	Model 3 Terner	Model 3 Wharton	Model 3 Terner	Model 3 Wharton
θ	0.123***	0.0827***	0.0562***	0.0672***
	(0.021)	(0.010)	(0.016)	(0.009)
ϕ	0.339***	0.413***	0.406***	0.457***
	(0.045)	(0.048)	(0.043)	(0.041)
Marginal Effect	Model 1 Terner	Model 2 Wharton	Model 3 Terner	Model 4 Wharton
Regulation Index	0.114***	0.0763***	0.0518***	0.0619***
(CALURI/TCLURI)	(0.019)	(0.009)	(0.014)	(0.008)
Log Income Per Capita	0.402***	0.509***	0.514***	0.573***
	(0.056)	(0.061)	(0.057)	(0.052)
Avg. Log Income Per	-0.104***	-0.131***	-0.131***	-0.146***
Capita	(0.014)	(0.015)	(0.014)	(0.013)
Endogenize	Income (4)	Income (4)	Income (4)	Income (4)
Instrument	Lag & Demo	Lag & Demo	Lag & Demo	Lag & Demo
Cities	Overlapping Cities	Overlapping Cities	Terner Cities	Wharton Cities
No. of Cities	102	102	234	179
N	608	608	1,404	1,144

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. A linear model is used to separate housing price variations due to housing, regional and macro controls in step 1, while GMM is used to estimate the model parameters in step 2. The estimation in step 1 is based on housing transactions from 2012 to 2017 in California. The controls used in step 1 include 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 days with good air quality. *Endogenize* indicates whether income or regulation is treated as endogenous. The number of instruments is listed in the parenthesis. The instruments used to endogenize a variable are listed under *Instrument*. *Demo* includes the share of high education, the population age, and the share of high-tech jobs.

Table 5d. Estimation of Non-linear Models: Parameters and Marginal Effects (1993-2017)

Parameters	Model 3	Model 4	Model 5
θ	0.0360***	0.0380***	0.0337***
	(0.009)	(0.007)	(0.008)
ϕ_1	0.396***	-6.043***	-1.789
	(0.026)	(1.595)	(1.910)
ϕ_2		0.838***	0.280
		(0.207)	(0.240)
δ_0		-7.324**	-2.443
		(3.325)	(3.167)
δ_1		2.113**	0.874
		(0.844)	(0.804)
Marginal Effect	**Model 3**	**Model 4**	**Model 5**
CALURI	0.0331***	-0.282**	-0.0849
	(0.008)	(0.121)	(0.110)
Log Income Per Capita	0.511***	-7.781***	-2.313
	(0.033)	(2.051)	(2.470)
Avg. Log Income Per Capita	-0.129***	1.969***	0.584
	(0.008)	(0.519)	(0.624)
CALURI*Log Income Per Capita		0.0804***	0.0294
		(0.031)	(0.028)
Sq. Log Income Per Capita		1.079***	0.362
		(0.267)	(0.311)
Sq. Avg. Log Income Per Capita		-0.273***	-0.0915
		(0.067)	(0.078)
Sq. Demeaned Log Income Per Capita			-0.177
			(0.377)
Demeaned Log Income Per Capita			0.00403
*Demeaned CALURI			(0.006)
Sq. Demeaned CALURI			-0.0000229
			(0.000)
N	4,620	4,620	4,620

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. A linear model is used to separate housing price variations due to housing, regional and macro controls in step 1, while GMM is used to estimate the model parameters in step 2. The estimation in step 1 is based on housing transactions from 1993 to 2017 in California. The controls used in step 1 include 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 days with good air quality.

Table 5e. Estimation of Non-linear Models: Parameters and Marginal Effects (2012-2017)

Parameter	Model 3	Model 4	Model 5
θ	0.0672***	0.0723***	0.0653***
	(0.009)	(0.008)	(0.010)
ϕ_1	0.457***	-7.246***	-1.520
	(0.041)	(1.320)	(28.764)
ϕ_2		0.976***	0.249
		(0.166)	(3.531)
δ_0		-4.619**	-1.606
		(2.459)	(4.670)
δ_1		1.380**	0.640
		(0.604)	(1.147)
Marginal Effect	**Model 3**	**Model 4**	**Model 5**
CALURI	0.0619***	-0.340**	-0.110
	(0.008)	(0.166)	(0.313)
Log Income Per Capita	0.573***	-9.031***	-1.907
	(0.052)	(1.628)	(36.105)
Avg. Log Income Per Capita	-0.146***	2.309***	0.487
	(0.013)	(0.417)	(9.210)
CALURI*Log Income Per Capita		0.0998**	0.0418
		(0.040)	(0.078)
Sq. Log Income Per Capita		1.216***	0.312
		(0.204)	(4.432)
Sq. Avg. Log Income Per Capita		-0.311***	-0.0796
		(0.052)	(1.131)
Sq. Demeaned Log Income Per Capita			-0.127
			(4.794)
Demeaned Log Income Per Capita			0.00430
*Demeaned CALURI			(0.070)
Sq. Demeaned CALURI			-0.0000365
			(0.000)
N	1,144	1,144	1,144

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. A linear model is used to separate housing price variations due to housing, regional and macro controls in step 1, while GMM is used to estimate the model parameters in step 2. The estimation in step 1 is based on housing transactions from 2012 to 2017 in California. The controls used in step 1 include 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 days with good air quality.

Table 6a. Comparison to Jackson (2018)

Jackson (2018)			
Housing market examined	366 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	PE channel	GE Channel	Total
Marginal effect of regulation on prices	6.76%	-0.57%	6.19%

Note: The price response to +1 SD of the regulation index in California in Jackson (2018) and in our paper come from their Table 3 and our Model 3 in Table 5f (2012-2017), respectively.

Table 6b. 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	PE Channel	GE Channel	Total
Marginal effect of regulation on prices	3.99%	-0.18%	3.80%

Note: The price response to +1 SD of the regulation index in the Bay Area in Quigley et al (2008) and in our paper comes from their Table 9.9 and our appendix table on housing price response to +1 SD increase in CALURI (1993-2017), respectively.

Table 7. Housing Price Responses (%) to +1 SD CALURI by MSA (2012-2017)

	Model 3 Constant Effect with Constant Neighboring Regulation			Model 4 Linear Approx. with Constant Neighboring Regulation			Model 5 Quadratic Approx. with Constant Neighboring Regulation			Model 5 Quadratic Approx. with MSA-Specific Neighboring Regulation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MSA	PE	GE	TE	PE	GE	TE	PE	GE	TE	PE	GE	TE
Bakersfield, CA	6.72	-0.53	6.19	4.47	-0.57	3.90	5.37	-0.64	4.74	5.21	-0.65	4.56
Chico, CA	6.72	-0.53	6.19	4.48	-0.57	3.92	5.38	-0.63	4.75	5.22	-0.64	4.57
Fresno, CA	6.72	-0.53	6.19	4.60	-0.57	4.03	5.43	-0.64	4.79	5.27	-0.65	4.62
Hanford-Corcoran, CA	6.72	-0.53	6.19	0.86	-0.57	0.29	3.86	-0.78	3.08	3.51	-0.81	2.70
Los Angeles-Long Beach-Anaheim, CA	6.72	-0.53	6.19	8.30	-0.57	7.73	6.97	-0.47	6.51	7.02	-0.46	6.56
Madera, CA	6.72	-0.53	6.19	1.23	-0.57	0.66	4.01	-0.77	3.25	3.68	-0.79	2.89
Merced, CA	6.72	-0.53	6.19	0.57	-0.57	0.01	3.74	-0.81	2.93	3.38	-0.84	2.53
Modesto, CA	6.72	-0.53	6.19	3.31	-0.57	2.75	4.89	-0.68	4.21	4.67	-0.70	3.97
Napa, CA	6.72	-0.53	6.19	7.14	-0.57	6.58	6.49	-0.52	5.97	6.47	-0.52	5.95
Oxnard-Thousand Oaks-Ventura, CA	6.72	-0.53	6.19	5.80	-0.57	5.23	5.93	-0.58	5.35	5.84	-0.59	5.25
Redding, CA	6.72	-0.53	6.19	5.15	-0.57	4.59	5.66	-0.60	5.05	5.53	-0.61	4.92
Riverside-San Bernardino-Ontario, CA	6.72	-0.53	6.19	2.94	-0.57	2.37	4.73	-0.70	4.03	4.49	-0.72	3.77
Sacramento-Roseville, CA	6.72	-0.53	6.19	6.72	-0.57	6.15	6.31	-0.54	5.78	6.27	-0.54	5.73
Salinas, CA	6.72	-0.53	6.19	4.93	-0.57	4.36	5.56	-0.61	4.95	5.43	-0.62	4.81
San Diego-Carlsbad, CA	6.72	-0.53	6.19	7.78	-0.57	7.22	6.76	-0.49	6.27	6.77	-0.48	6.29
San Francisco-Oakland-Hayward, CA	6.72	-0.53	6.19	9.41	-0.57	8.84	7.44	-0.42	7.02	7.54	-0.41	7.13
San Jose-Sunnyvale-Santa Clara, CA	6.72	-0.53	6.19	10.89	-0.57	10.33	8.06	-0.35	7.71	8.24	-0.33	7.91
San Luis Obispo-Paso Robles, CA	6.72	-0.53	6.19	6.74	-0.57	6.17	6.32	-0.54	5.78	6.28	-0.54	5.74
Santa Cruz-Watsonville, CA	6.72	-0.53	6.19	5.19	-0.57	4.62	5.67	-0.60	5.07	5.55	-0.61	4.94
Santa Maria-Santa Barbara, CA	6.72	-0.53	6.19	7.29	-0.57	6.73	6.55	-0.51	6.04	6.54	-0.51	6.03
Santa Rosa, CA	6.72	-0.53	6.19	6.16	-0.57	5.60	6.08	-0.57	5.52	6.01	-0.57	5.44
Stockton-Lodi, CA	6.72	-0.53	6.19	2.94	-0.57	2.38	4.73	-0.70	4.03	4.49	-0.72	3.77
Vallejo-Fairfield, CA	6.72	-0.53	6.19	3.68	-0.57	3.12	5.04	-0.67	4.38	4.84	-0.68	4.16
Visalia-Porterville, CA	6.72	-0.53	6.19	1.93	-0.57	1.37	4.31	-0.74	3.57	4.02	-0.76	3.25
Yuba City, CA	6.72	-0.53	6.19	1.23	-0.57	0.67	4.02	-0.78	3.24	3.69	-0.81	2.87

Note: percentage deviation (%) of MSA housing prices to +1 SD of CALURI. The total effect (TE) is decomposed into the partial equilibrium effect (PE) and the general equilibrium effect (GE). *Constant Effect* is based on Model 3 in Table 5. *Linear Approximation* and *Quadratic Approximation* indicate the type of method to approximate the log moving probability in the estimation of the housing price equation of Models 4 and 5 in Table 5. The estimation is based on housing transactions from 2012 to 2017 in California. The quadratic specification uses the average real per capita income from 2012 to 2017 to derive the PE and GE effects. Models 3 and 4 assumes constant neighboring regulation (average regulation in California), while Model 5 assumes the neighboring regulation of a city to be the average regulation of the MSA where a city is located.

Table 8. Counterfactual Price Changes (%) in Response to Relaxing Regulation (2012-2017)

City CALURI	Los Angeles City (3.38)		San Francisco City (1.04)		San Diego City (0.30)	
Scenario	MSA Mean (-0.20)	MSA Min (-1.89)	MSA Mean (-0.22)	MSA Min (-3.23)	MSA Mean (-0.25)	MSA Min (-1.04)
PE (%)	-24.95	-36.77	-9.36	-31.78	-3.76	-9.04
GE (%)	1.72	2.50	0.53	1.76	0.27	0.65
TE (%)	-23.23	-34.27	-8.83	-30.02	-3.49	-8.39

Note: the experiment considers relaxing city regulation to the MSA mean or minimum regulatory level. The price change attributed to the partial equilibrium (PE) is defined as the difference of the PE effect in the counterfactual case with the relaxed regulatory level and the PE effect without regulatory change. The price change attributed to the general equilibrium (GE) effect is defined in a similar way. The total price change (TE) is the sum of the price change attributed to PE and GE effects. The estimation is based on housing transactions from 2012 to 2017 in California. The model specification is based on Model 4 in Table 5f with the quadratic-approximated log moving probability and uses the average per capita income from 2012 to 2017 to derive the PE and GE effects.

Table 9. Log Housing Price and Regulatory Impacts in Greater Los Angeles

	(1)	(2)	(3)	(4)	(5)	(6)
CALURI	0.0670***	0.162***	0.111***	0.192***	-0.00385	-0.00932
	(0.0014)	(0.0074)	(0.0019)	(0.0076)	(0.003)	(0.011)
RRI		0.0964***		0.0827***		-0.00517
		(0.0073)		(0.0074)		(0.010)
Has High Neighboring					0.0961***	0.0987***
CALURI					(0.005)	(0.007)
CALURI * Has High					0.0706***	0.0706***
Neighboring CALURI					(0.003)	(0.003)
Endo. Regulation	No	No	Yes	Yes	No	No
Adjusted R^2	0.563	0.556	0.565	0.558	0.569	0.569
N	61,263	61,263	61,263	61,263	61,263	61,263

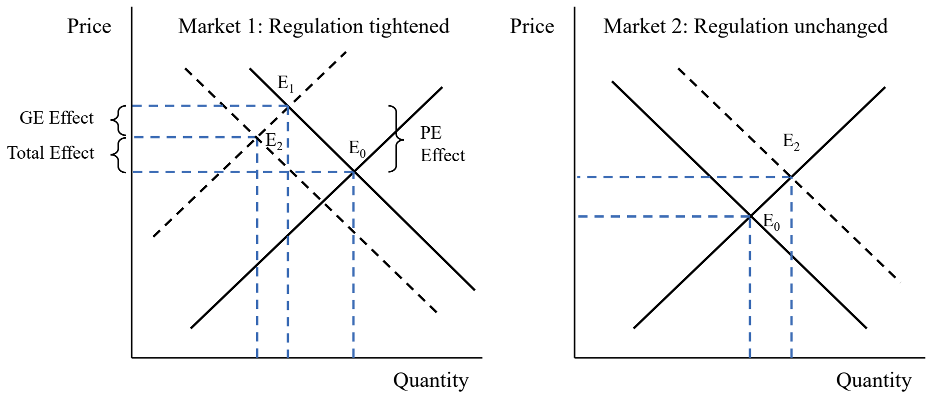
Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. The dependent variable is the log housing prices. Omitted control variables in regression models include log city-level per capita income where a property is located and its squared term, the number of bedrooms, the number of bathrooms, log mile distance to the nearest core city, the property age, the property type (single family/condo), the property size, log mile distance to the Pacific coast, the number of days with good air quality. The sample is the property sales in Los Angeles, Orange and Ventura counties in 2016. *Has High Neighboring CALURI* is a binary variable indicating cities whose neighboring regulation is larger than 75th percentile. *Endo. Regulation* indicates whether CALURI (and RRI) is endogenized using political preference. The voting share for Republicans in the 2004 US Presidential Election is used as the instrument to endogenize regulation.

Table 10. Log Housing Price in Los Angeles MSAs by Per Capita Income

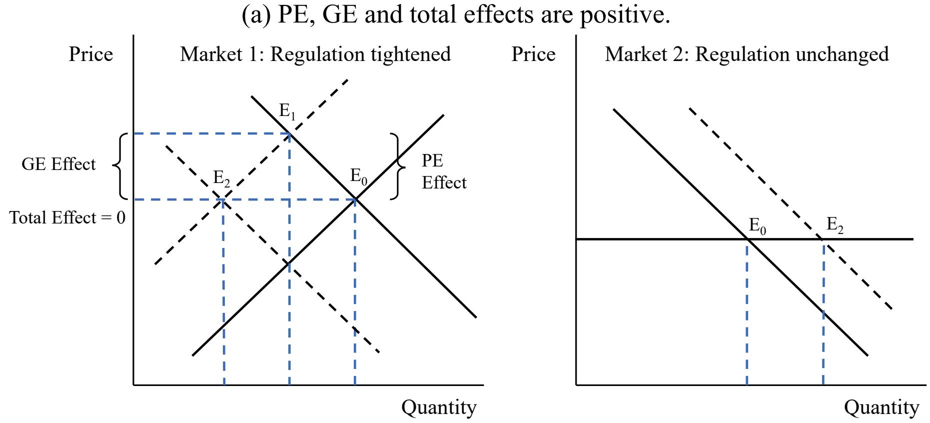
	(1) ≤ Median	(2) > Median	(3) ≤ Median	(4) > Median	(5) All	(6) All
CALURI	0.0154***	0.0395***	0.150***	0.141***	0.149***	0.172***
	(0.002)	(0.006)	(0.012)	(0.015)	(0.009)	(0.011)
RRI			0.133***	0.105***	0.126***	0.150***
			(0.011)	(0.014)	(0.009)	(0.011)
CALURI * Has					0.00035	
High Income					(0.005)	
RRI * Has High						-0.0491***
Income						(0.018)
Adjusted R^2	0.519	0.680	0.520	0.682	0.602	0.602
N	39,345	13,945	39,345	13,945	53,290	53,290

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. The dependent variable is the log housing prices. 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, log mile distance to the Pacific coast, the number of days with good air quality. The coefficients on the linear and quadratic terms of log per capita income are allowed to vary by the income group. The sample is the property sales in Los Angeles and Orange counties in 2016. *Has High Income* is an indicator that cities has per capita income above the median in the Los Angeles MSA.

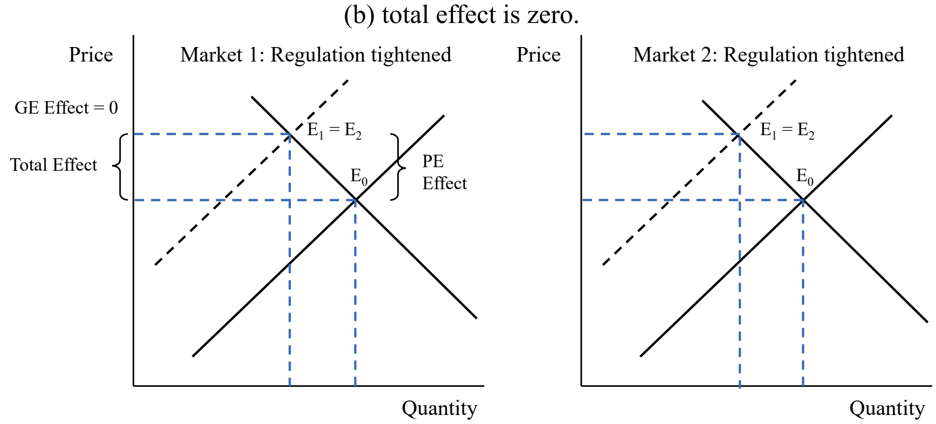
Figures



(a) PE, GE and total effects are positive.



(b) total effect is zero.



(c) GE effect is zero.

Figure 1: graphical illustration of regulatory impact on housing prices. Panel (a): 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 (PE) channel. The change from E_1 to E_2 shows the general equilibrium (GE) effect that reallocates housing demand between two markets. E_1 is the partial equilibrium and would be the new equilibrium if housing markets were segmented. Panel (b): the example is similar to the one in Panel (a) except that the GE effect in absolute value is as strong as the PE effect. That the total effect of regulation is zero does not mean that regulation is irrelevant to housing prices. Panel (c): the example considers tightening regulation in by the same amount in two markets. The GE effect is zero.

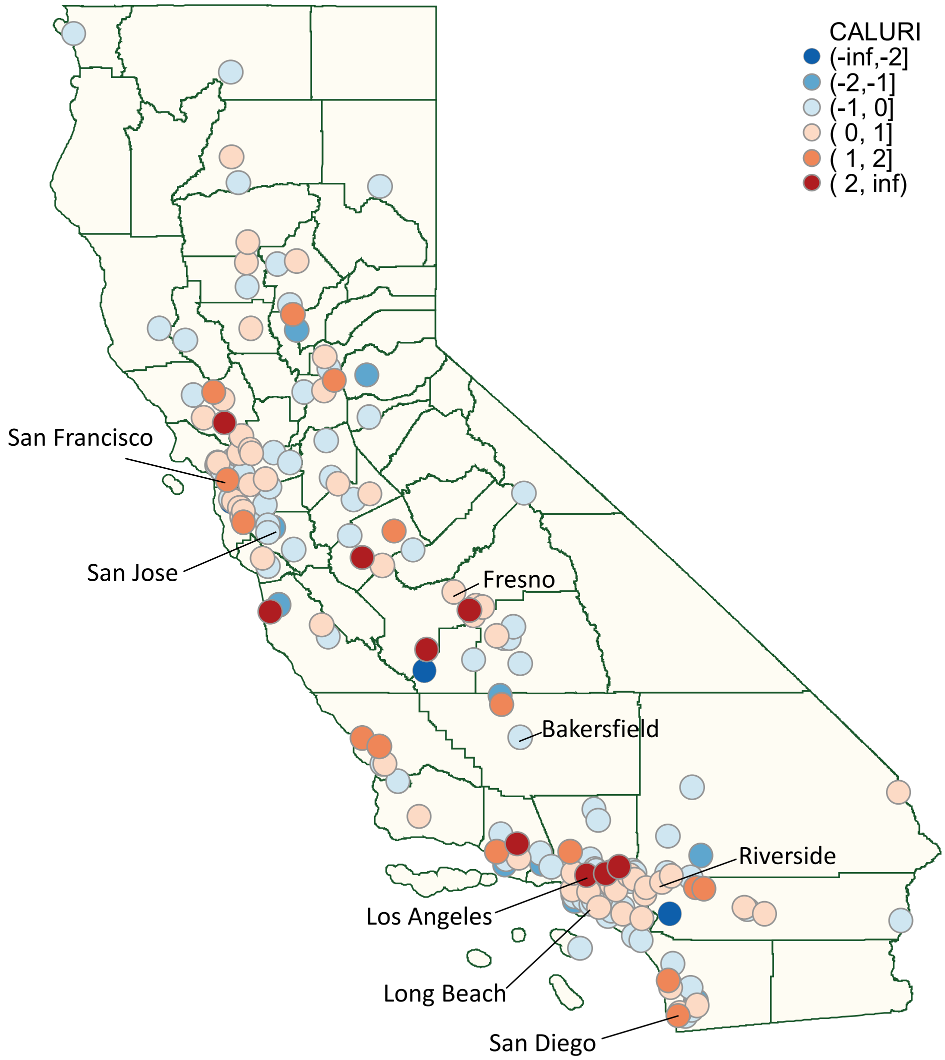
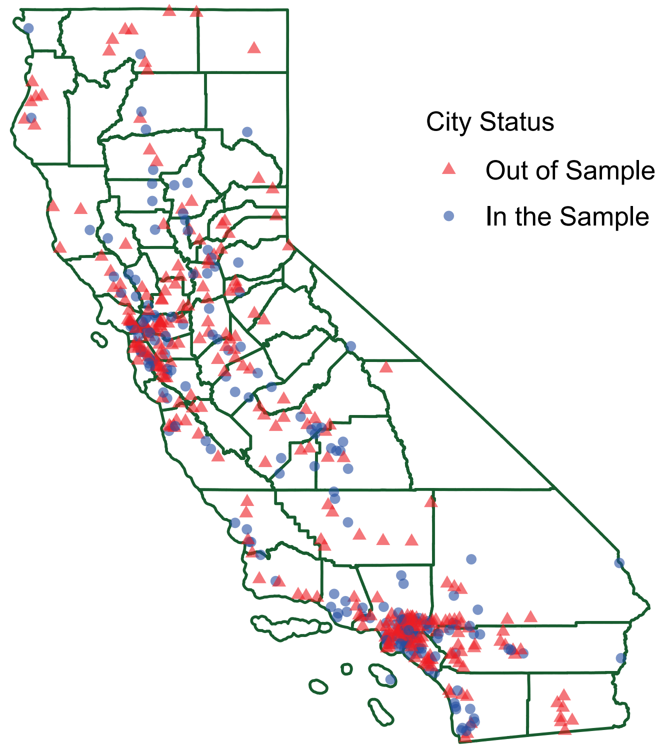
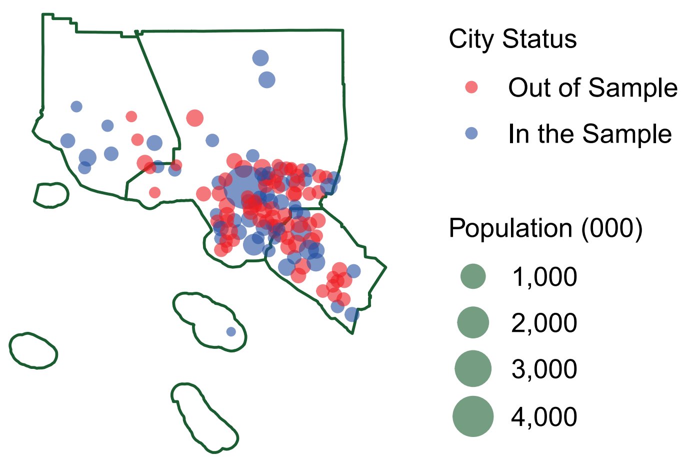


Figure 2: spatial distribution of land use regulation intensity in California. California Land Use Regulation Index (CALURI) is based on the sub-indices from WRLURI. A higher index value indicates higher regulation intensity. There are 185 jurisdictions in total.

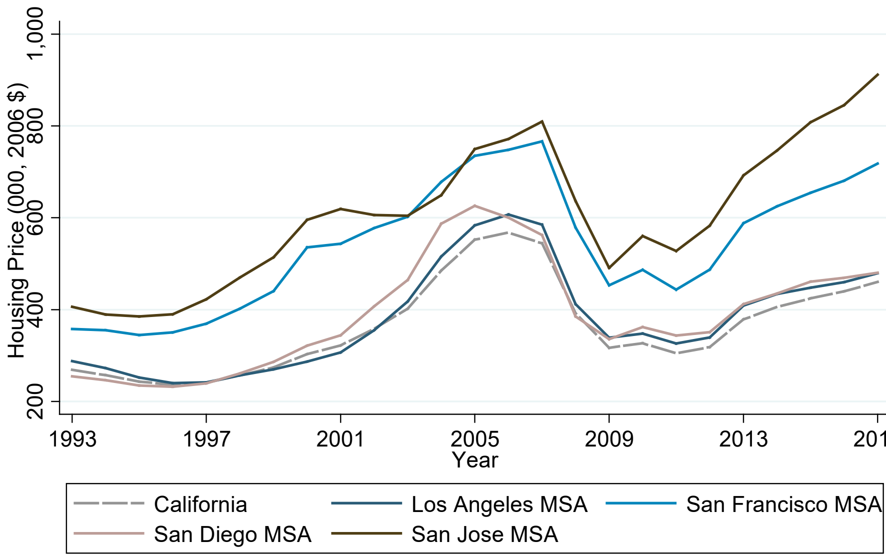


(a) California

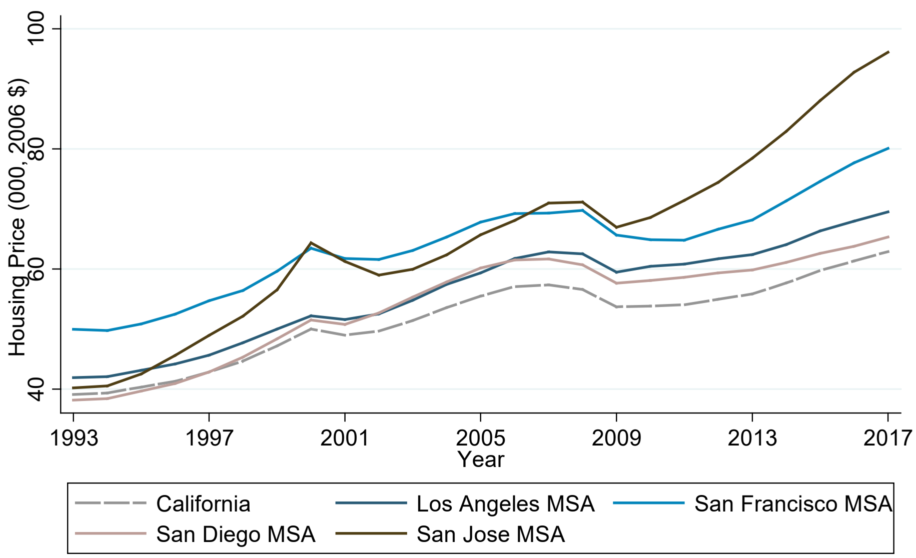


(b) Ventura, Los Angeles, and Orange counties (from northwest to southeast)

Figure 3: Panel (a): spatial distribution of cities in and out of the sample. Green lines denote county boundaries. There are 482 cities in California. Transactions in 185 cities available in the Wharton survey (Gyouko et al, 2008) are used in analysis. Panel (b): spatial distribution of cities in and out of the sample in Ventura, Los Angeles, and Orange counties. There are 122 cities in the selected counties with 55 cities available in the Wharton survey. Data on city population is based on the ACS 2012-2016 5-year Tract Summary File.

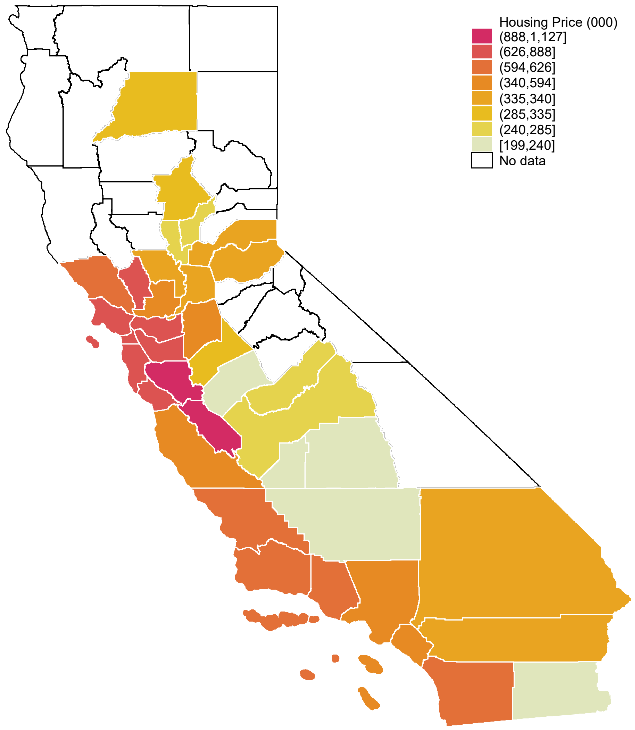


(a) Real Housing Prices of Selected MSAs (2006 $)

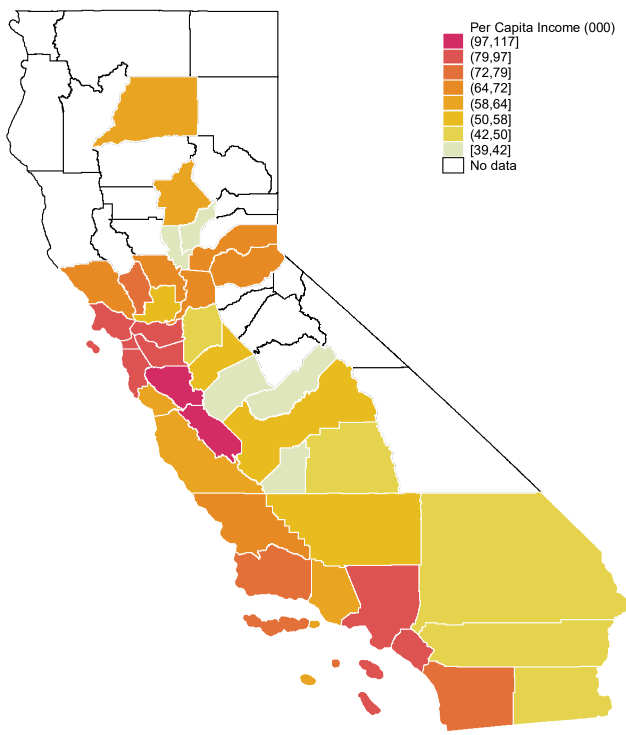


(b) Real Per Capita Income of Selected MSAs (2006 $)

Figure 4: Time trend of real housing prices of California and selected MSAs (Panel a) and time trend of real per capita income of California and selected MSAs (Panel b). The dollar values are adjusted for inflation to 2006 dollars.

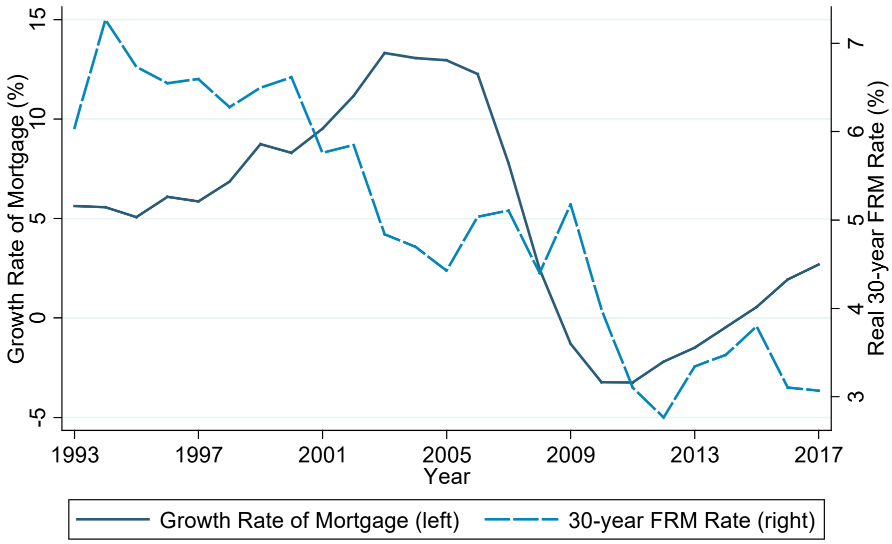


(a) Housing Prices (2017)

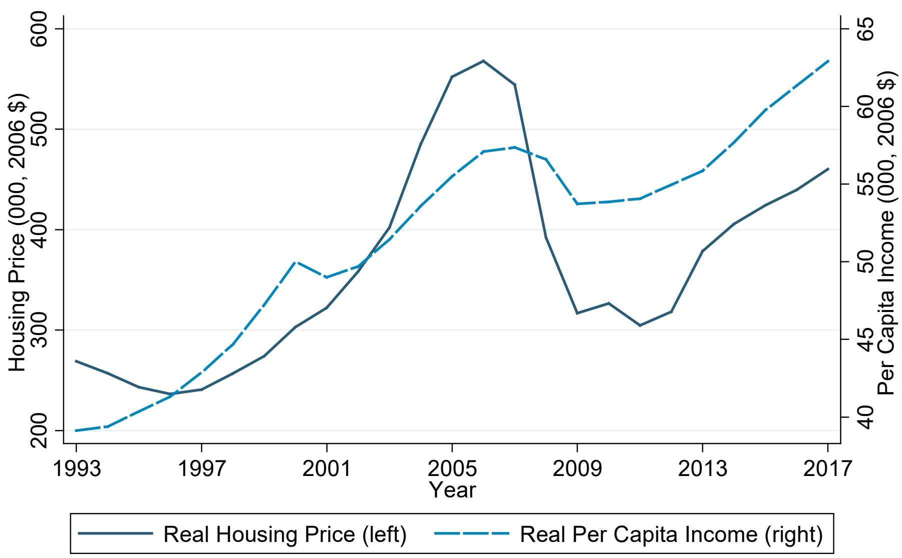


(b) Per Capita Income (2017)

Figure 5: Average housing prices and per capita income by MSA in 2017. The white lines denote county boundaries. Dollars are in nominal term.

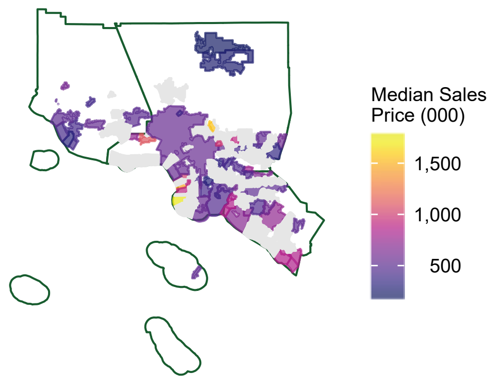


(a) Growth Rate of Mortgage and Real 30-year FRM Rate

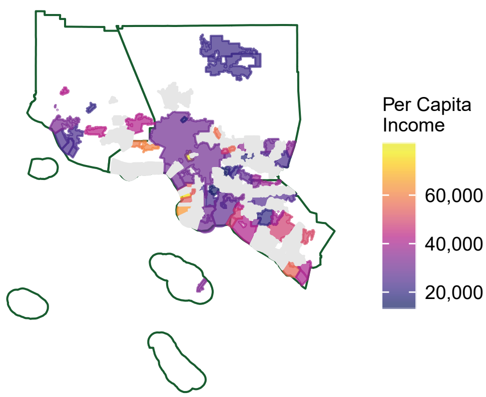


(b) Real Housing Price and Real Per Capita Income

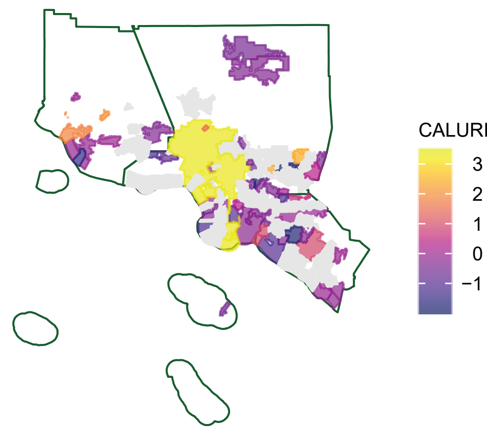
Figure 6: Panel (a) show the time trend of macro variables: annual growth rate of residential mortgage debt of US households and 30-year real US average fixed-rate mortgage rate. The mortgage rate has deducted annual inflation. Panel (b) shows the time trend of real housing prices and the real per capita income. The dollar values are adjusted for inflation to 2006 dollars.



(a) Median Sales Price

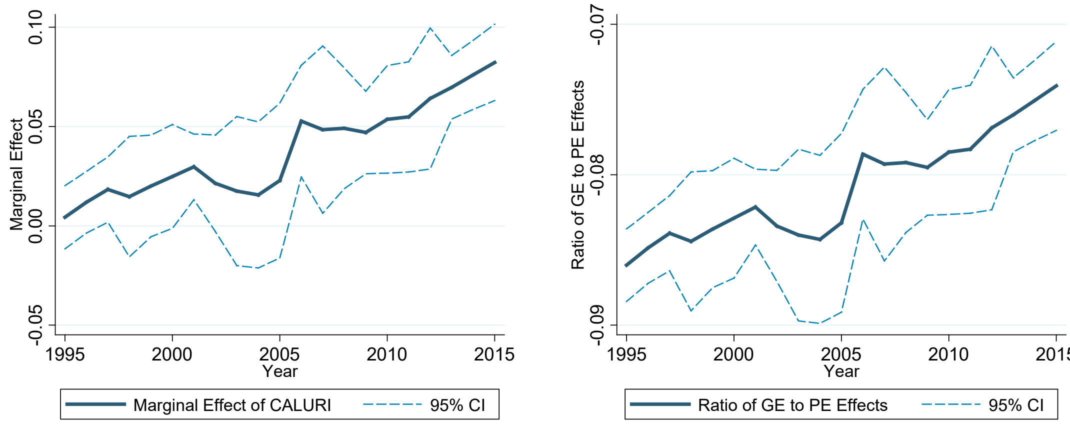


(b) Per Capita Income



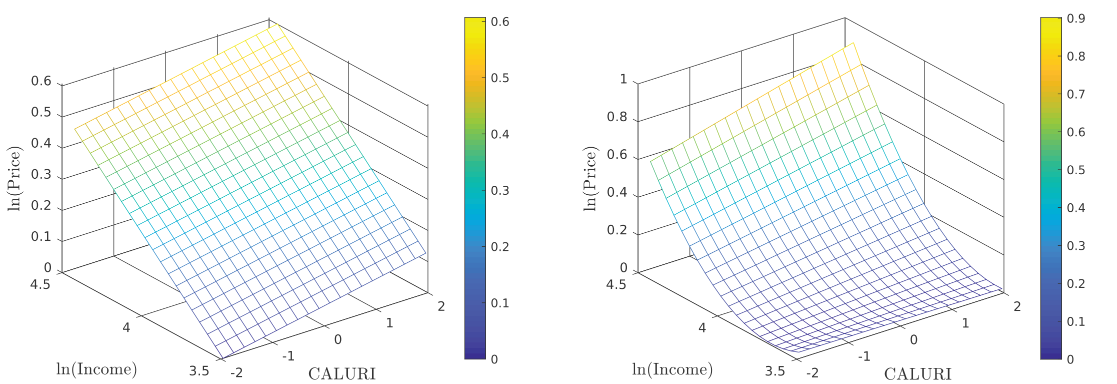
(c) CALURI

Figure 7: Heat maps of cities in Ventura, Los Angeles, and Orange counties (from northwest to southeast). Median sales price of each city (2016 dollars) is derived from the residential transaction prices in 2016 from ZTRAX. Per capita income (2016 dollars) comes from 2012-2016 5-year ACS. Cities covered by the 2008 Wharton survey are included (gray area for missing cities). For visualization of variables for all cities in the counties, see the appendix.



(a) Marginal Effect of CALURI (b) Ratio of GE to PE Effects

Figure 8: Marginal effect of CALURI on log housing prices (Panel a) and the ratio of GE and PE effects (Panel b) by year. Estimation of the marginal effects is based on Model 3 in Table 5 which involves 2 steps. Step 1 of the estimation takes out the housing price variation attributed to housing, regional (except CALURI and per capita income for Step 2) and macro characteristics (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 mile distance to the Pacific Coast). Step 2 of the estimation is based on GMM estimation. The marginal effects of CALURI, PE and GE effects are derived using a subsample within a 3-year moving bandwidth. The dashed lines represent the 95% confidence interval.



(a) Linear Model (b) Nonlinear Model

Figure 9: log price surface as a function of the log GDP per capita (ln(Income)) and land use regulation (CALURI). The grid is simulated using normal distribution, with the mean and the standard deviation estimated from the data. Grid points within 95% confidence intervals ($\pm 1.96\sigma$) along each dimension are plotted. Panels (a) and (b) are based on Models 3 and 4 in Table 5e for the 1993-2017 sample respectively.

Appendix: Local Land Use Regulation and Housing Prices: How Relative Restrictiveness and Income Matter

Desen Lin and Susan Wachter

A.1 Data Description

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.

A.1.1 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 et al (2008).[1] 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 25%. We report the response rate by MSA in California below.

We focus on the cities in California that are covered by the Wharton survey, because the coverage of regulation data and the housing data in California is much better than that in other states.[2] Cities in California appear to vary greatly in their degree of land use regulation, creating sufficient variations of regulatory stringency (Fischel, 1995). We follow the majority of the literature to treat regulation as exogenous in our study. However, we do consider endogenizing regulation using political preference as an instrument (Quigley et al, 2008), and find comparable results for the estimated regulatory impact, whether instrumented or not.[3] 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. 184 out of 185 cities responded to the Wharton survey have at least one transaction record in ZTRAX. The only city in the Wharton survey not matched to ZTRAX is Crescent City. While WRLURI covers only a limited

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

[2] 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.

[3] In Section 6 of the main paper, using the voting share for the Republican party in the 2004 US Presidential Election as the instrument of regulation, we find comparable and upward adjustment of the estimated regulatory effect, which is consistent with the literature (Ihlanfeldt, 2007; Quigley et al, 2008). We don't assume endogenous regulation in most of our study because of the weak instrumental variable issue.

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).[4] 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 use 8 sub-indices that have cross-city variation to construct a single measure of regulation (CALURI), including the 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).[5] We show the density distribution of 8 sub-indices in Figure A1.

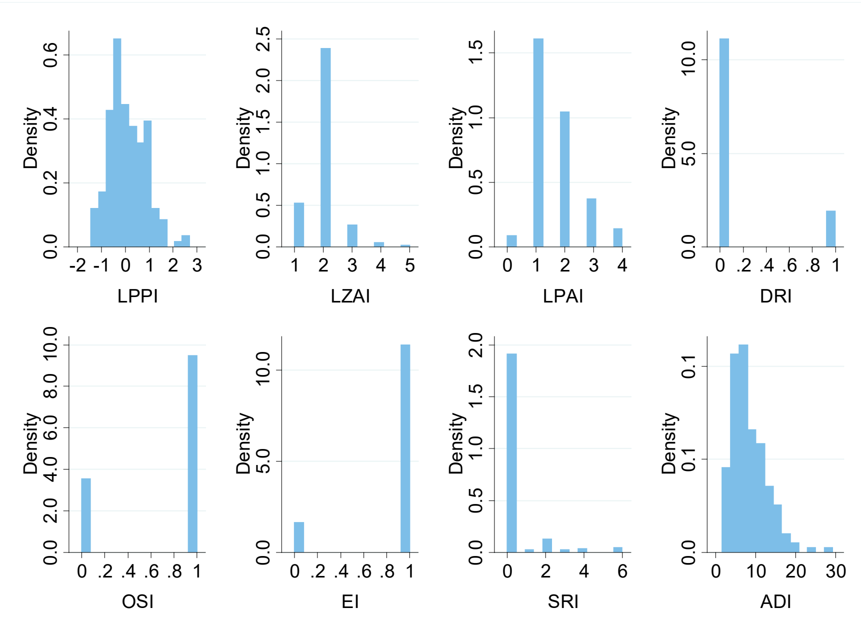


Figure A1: density distribution of the 8 sub-indices underlying the California Land Use Regulation Index (CALURI). Source: Gyourko, Saiz and Summers (2008) and authors' calculation.

In Figure A2, we show the kernel density of CALURI and WRLURI 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. WRLURI lies to the right of CALURI, meaning that cities in California are more regulated than the US average. We list the estimated CALURI by MSA and city at the end of the appendix (Table A16). In Figure A3, we compare

[4] 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 A1.
[5] 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).

CALURI with WRLURI. We show that CALURI is highly positively correlated with WRLURI and the simple sum of the 8 standardized sub-indices underlying CALURI, so the method of constructing the regulatory index is not driving the unidimensional measure of regulation.

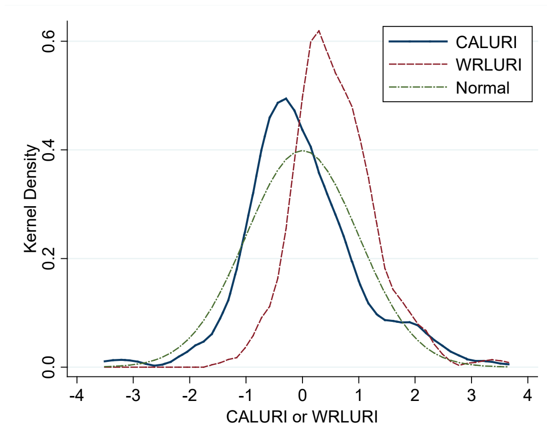
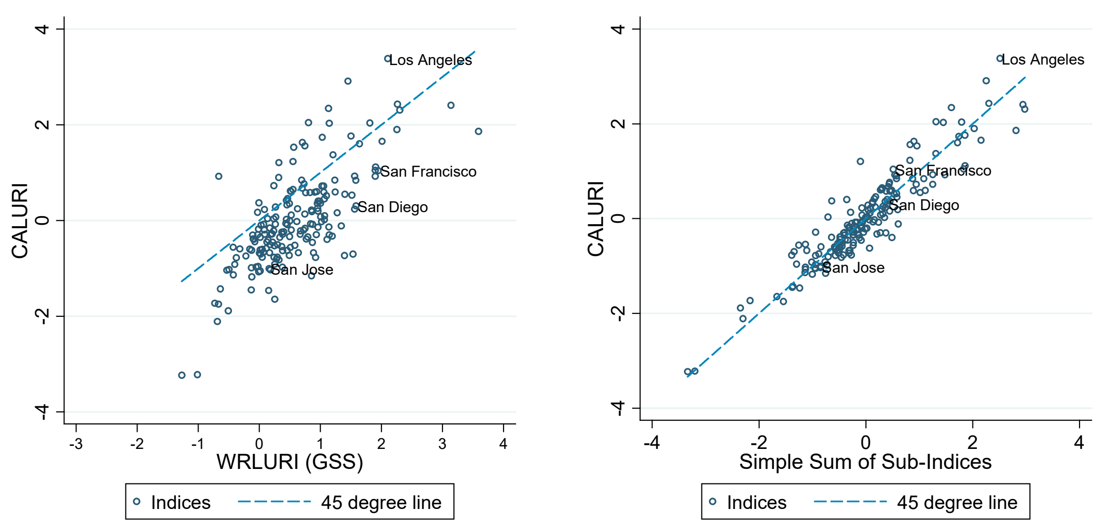


Figure A2: comparison of the kernel density of California Land Use Regulation Index (CALURI), Wharton Index (WRLURI) with California cities and the normal density. CALURI is based on the 8 sub-indices in WRLURI that exhibit intra-state variation. A higher index value indicates higher regulation.



(a) CALURI vs WRLURI (b) CALURI vs Simple Sum of Sub-indices

Figure A3: scatter 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)

Table A1. 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 cities in California, 458 of which are assigned to a CBSA. “CA” and “GSS” counts the total number of cities 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.1.2 Housing Data

For the housing data, we rely on the Zillow Transaction and Assessment Dataset (ZTRAX). 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. We are interested in the transaction prices in the deed transfers and the housing characteristics in property assessment data in California from 1993 to 2013.

Particularly, we restrict the data to observations with residential property sales that have detailed documentation of housing characteristics. We include the following housing characteristics: the transaction date, the property use, the number of bedrooms, the number of bathrooms, the property age, the property size and the distance to the Central Business District (CBD). Besides, the summary statistics in the main paper, Figure A2 reports the distribution property use in and out of our sample. We exclude short sale transactions that will greatly affect the housing price metrics (FHFA, 2012).[6] We compute the property age, the property size and the distance to the nearest core cities that are not directly observable in ZTRAX. The property age is calculated as the difference of the transaction year and the built year. There are multiple fields measuring different aspects of the property size, 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 next section.

Table A2. Distribution of Residential Property Use

	Land Use Sample		Out of 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.

A.1.2.1 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. We first restrict the sample to the transaction with the sales prices more than 5,000 US dollars in California. California data before

[6] We can identify those distress sales that occur at significant discounts compared with other transactions. FHFA HPI report in 2012Q1 (p.12) indicates that FHFA HPI includes short sales but distress sales can substantially affect housing prices metrics. FHFA plans on releasing a set of distress-free indexes but is constrained by the available data to identify distress sales especially for earlier transactions. One option suggested by FHFA is to construct the index using only transactions that are known definitively to be non-distressed, which we follow in the paper.

1993 (inclusive) is extremely sparse, so our ZTRAX data starts from 1993 and ends in 2017. 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 90% of the transactions are matched to the assessment files. We recode the property use into three main categories: single-family residential, condominium and others. The number of bedrooms/bathrooms are recoded into 6 levels (0, 1, 2, 3, 4, 5+), while the property age is divided into 10 levels (0, 1-5, 6-10, 11-20, 21-30, 31-40, 41-50, 51-60, 61-70, > 70).

There is no separate field to directly observe the property size, so we construct the field as follows. We are able to observe the following fields relevant to the property size: 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. We calculate the maximum of the fields above and define it as the square footage of a property.

The mile distance to CBD is defined as the miles of a property to the nearest core city 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.[7] We assign these cities to the nearest MSAs, so they don't fall out of sample in the analysis. 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.

[7] 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.

A.1.3 Additional Data for the Analysis of California

A.1.3.1 Regional Data

We calculate per capita income based on data from Moody's Analytics. Moody Analytics compiles per capita income 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. We use GMP and population from Moody's data to calculate per capita income. Both GMP and population data are annual. Ideally, we would use city-level estimates. We use the MSA-level estimates instead, because the city-level series are not available in general and are not long enough to cover the time periods in our data sample.[8] 179 out of 185 cities responded to the Wharton Land Use Survey are matched to an MSA in Moody's data, because Moody Analytics only covers regional statistics in the metropolitan instead of micropolitan areas.[9]

The number of days with good air quality by year and MSA comes 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 days with good air quality (out of 365 days) as our measure of air quality, because this measure is easy to interpret. For earlier years and MSAs without daily observations, we calculate the share of days with good air quality in the total number of observed days and multiply the share by 365. Moreover, this measure is highly correlated with other air quality measures (the annual median or maximum Air Quality Index (AQI), days with NO_2, days with PM 2.5 etc).

To deal with the concern of endogenous per capita income, we endogenize per capita income using additional regional information as instrumental variables. Besides the lag term of per capita income as a natural instrument, we additionally include three demographic variables: the share of high education including college and graduate education for at least one year, the average population age, and the share of high-tech jobs. Data on the share of high education and the average population age come from the American Community Survey (ACS) 1-year Micro data from IPUMS USA.[10] Data on the share of high-tech jobs are compiled by Moody's Analytics, based on Bureau of Labor Statistics and Bureau of Economic Analysis.[11] Tables A3 and A4 report the summary statistics of the instrumental variables and the correlation with per capita income, respectively.

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[8] 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).

[9] 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.

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

[11] The definition of high-tech jobs from the Moody's dataset is based on NAICS code as follows: Pharmaceutical and Medicine Manufacturing (3254), Computer and Peripheral Equipment Manufacturing (3341), Communications Equipment Manufacturing (3342), Semiconductor and Other Electronic Component Manufacturing (3344), Navigational,

Table A3. 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 A4. 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.

A.1.3.2 Macroeconomic Data

We consider the impact of time varying factors on housing prices by including two macro variables: the growth rate of household mortgages in the US and the US 30-year fixed-rate mortgage rate. In Figure A5, we plot 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 fixed-rate mortgage rate comes from Primary Mortgage Market Survey by Freddie Mac.

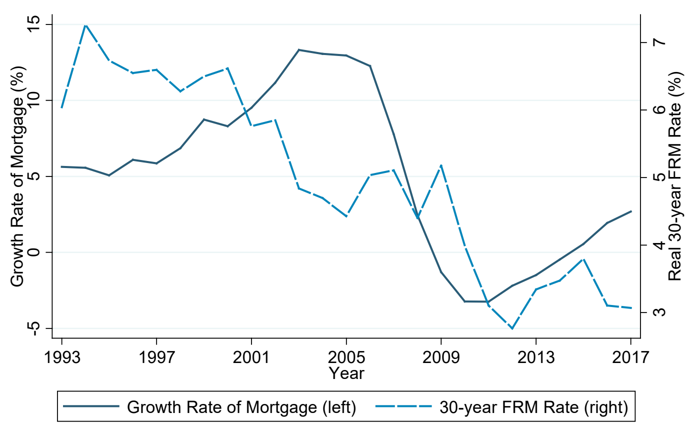


Figure A5: Annual growth rate of the residential mortgage debt of US households and 30-year US average fixed-rate mortgage rate. The mortgage rate has been adjusted for inflation. Source: Z.1 Financial Account Table from the Board of Governors of Federal Reserves and Freddie Mac.

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).

A.1.4 Additional Data for the Analysis of Greater Los Angeles

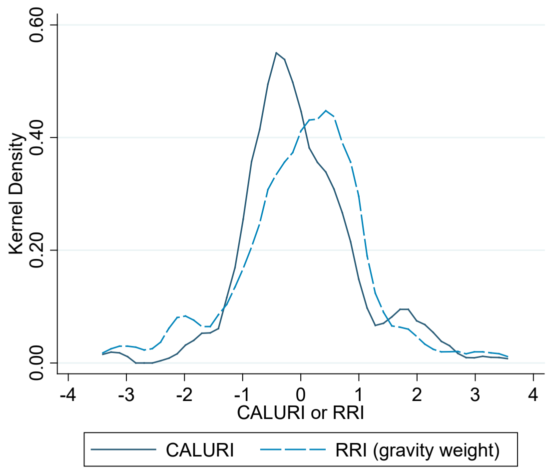
We collect census tract data from the American Community Survey (ACS) 2016 5-year tract summary file and aggregate it to the city-level. The 5-year estimates rely on the data from 2012 to 2016 but do not represent the statistics of any single year. We estimate the city-level statistics by averaging the tract-level counterparts using the tract population as the weight. Besides per capita income, other city-level variables we examine in the appendix include the homeownership rate, the share of Hispanic households, the voting share for the Republican party and the property tax rate. We collect precinct-level data on the political preference in the 2004 and 2016 US presidential elections. The former election is closer to the year of the Wharton survey and the data comes from the Harvard Election Data Archive, while the latter is closer to the year of property sales we look at and the data comes from the MIT Election Data and Science Lab. We aggregate the tax-rate-area-level to the city-level data on the property tax rate for the fiscal year 2015-2016 from the auditor-controller offices of each county website.[12]

We select 3 contiguous counties in the Greater Los Angeles—Los Angeles, Orange and Ventura counties—that have sufficiently high response rates in the Wharton survey and have a large number of cities. The response rate by metro area in California is listed in the table below. The selected counties cover 55 California cities or 30% of 185 cities in the Wharton survey. We show the kernel densities of CALURI and RRI with unimodal shapes and fat tails in Figure A6(a) and the negative correlation of CALURI and RRI (equal to -0.93) by a scatter plot in Figure A6(b) for available California cities. We separately mark the cities in the 3 selected counties (Los Angeles, Orange, Ventura) and show that the negative correlation still holds within each county.

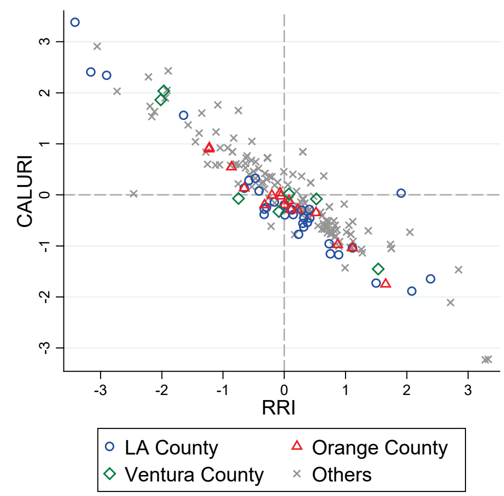
A.1.5 Visualization

In Figure A7, we visualize on a heat map the median sales prices in 2016 for all cities in the selected counties. In Figure A8, we visualize other city-level statistics, including per capita income, CALURI, homeownership rate, share of Hispanic households, political preference for the Republican party and property tax rate respectively.

[12] For Los Angeles County, see http://auditor.lacounty.gov/property-tax-report-central/. For Orange County, see http://www.ronforhomes.com/property%20taxes.htm. For Ventura County, see https://www.ventura.org/auditor-controllers-office/tax-rates-and-info/.



(a) Kernel Density



(b) CALURI vs RRI

Figure A6: Panel (a): 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. Gravity weight is used to define RRI, which is proportional to the per capita income and the inverse of squared distance. Panel (b) scatter plot of CALURI and RRI. Cities in 3 counties (Los Angeles, Orange and Ventura) are highlighted.

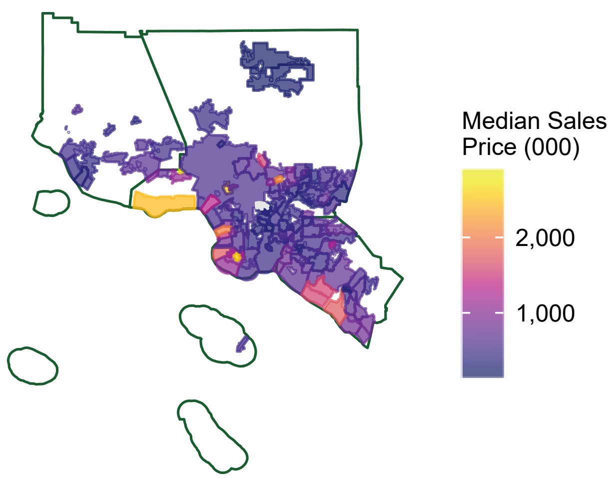


Figure A7: Median sales prices in Los Angeles, Orange and Ventura counties. Median sales price of each city (2016 dollars) is derived from the residential transaction prices in 2016 from ZTRAX.

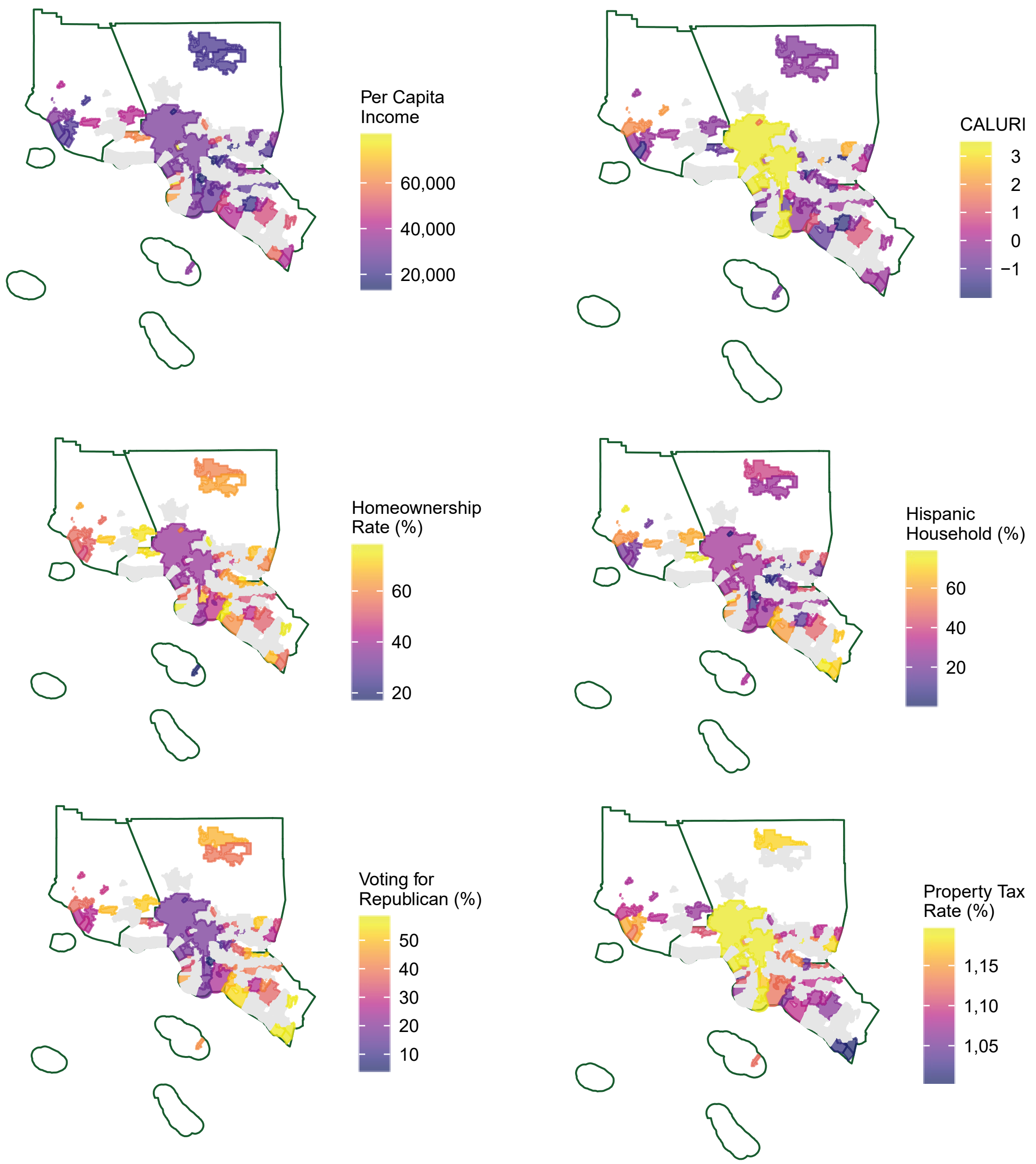


Figure A8a: Heat maps of cities in Los Angeles, Orange and Ventura counties. Per capita income, the homeownership rate and the share of Hispanic households come from 2012-2016 5-year ACS. Voting share for the Republican party is based on the 2004 US presidential election data from Harvard Election Data Archive. Property tax rates is collected from the controller offices on the county websites. Cities covered by the 2008 Wharton survey are included (gray area for missing cities). For visualization of variables for all cities in the counties, see the appendix.

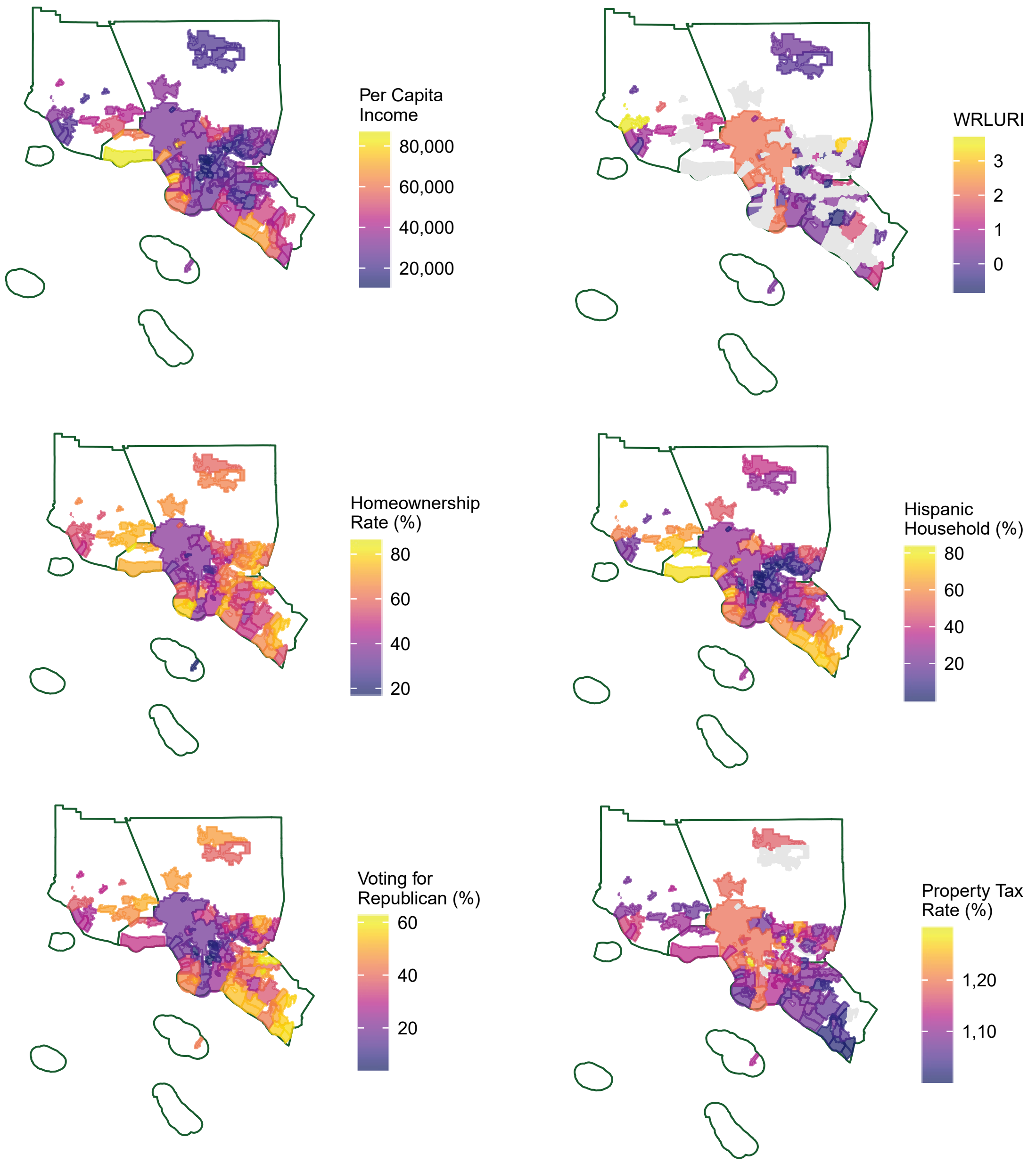


Figure A8b: Heat maps of cities in Los Angeles, Orange and Ventura counties. Per capita income, the homeownership rate and the share of Hispanic households come from 2012-2016 5-year ACS. Voting share for the Republican party is based on the 2004 US presidential election data from Harvard Election Data Archive. Data on the property tax rates is collected from the controller offices on the county websites.

A.2 Foundation and Extension of Housing Price Equation

A.2.1 A Micro Foundation of the Production Technology

We provide a micro foundation of the production technology in the housing developer's problem. 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 of L in the main paper.

$$\max_{L_j} A_0 p_j N^{(1-\sigma)\varepsilon} \int_0^{L_j} \theta\iota^{\theta-1} d\iota - c_j \int_0^{L_j} 1 d\iota - r_N N$$

A.2.2 Marginal Cost of Housing Supply

Motivated by the finding in the literature, we generalize the log marginal cost of housing production with the following multiplicative form.[13] [14]

$$\ln c_j = (\delta_1 z_j + \delta_0) \ln \tau_j + \ln c_0 \tag{1}$$

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 class of the models that include the benchmark model as a special case.

$$\delta_1 E_t(z_{0t}) + \delta_0 = 1 \tag{2}$$

For a property located in an MSA with the log income equal to $E_t(z_{0t})$, *ceteris paribus*, the marginal effect of regulation 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 extended log price equation will be similar, but with an additional interactive term of CALURI and the log per capita income.

[13] 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.

[14] 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.

A.2.3 Income Elasticity of Housing Demand

We extend the assumption of constant income elasticity of housing demand, captured by the parameter ϕ in the benchmark model. The extension results in the quadratic term of the log per capita income in the price equation. The household income adjusted by the demand shifter can be written as $\exp(\phi z)$. We extend the linear form to the quadratic form in the power term.

$$\exp(\phi_0 + \phi_1 z + \phi_2 z^2) = Z\exp(\phi_0)Z^{\phi_2 z + \phi_1 - 1} \tag{3}$$

where the income elasticity of housing demand is $2\phi_2 z + \phi_1$ in this case. With $\phi_0 = 0$ and $\phi_2 = 0$, we go back to the benchmark case. When $\phi_2 > 0$, the income elasticity is higher for wealthier cities. For computation, there are three parameters. We will identify ϕ_1 and ϕ_2, ϕ_0 will remain unidentified and be absorbed in the constant term. The extended log price equation will be similar, but with a quadratic term of the log per capita income and a quadratic term of the mean of the log per capita income.

A.3 Proof of Uniqueness of the Equilibrium and Derivation of the Estimation Equation

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

$$q_j = b_j p_j(q_j)^{\frac{1}{1-\theta}},\ \text{where } b_j = \frac{A_0^{\frac{1}{1-\theta}}}{\alpha Y_0 Z_j^{\phi}}\left(\frac{\theta}{c_j}\right)^{\frac{\theta}{1-\theta}} \tag{4}$$

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

$$q_j x = Z_j^{\phi} p_j(q_j)^{-\alpha},\ \text{where } x = \sum\nolimits_{k\in S} Z_k^{\phi} r_k^{-\alpha} \tag{5}$$

Combine two equations and eliminate p_j.

$$q_j(x) = Z_j^{\frac{\phi}{\alpha(1-\theta)+1}} b_j^{\frac{\alpha(1-\theta)}{\alpha(1-\theta)+1}} x^{-\frac{1}{\alpha(1-\theta)+1}} \tag{6}$$

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.

$$\sum\nolimits_{k\in S} q_j(x) = 1 \tag{7}$$

LHS of (4) is a strictly decreasing function of x, while RHS is a weakly increasing function of x. There is a unique solution to the equation. Given x, we can solve the set of moving probabilities.

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

$$q_j = \frac{(Z_j^{\phi})^{1-\lambda} b_j^{\lambda}}{(Z_j^{\phi})^{1-\lambda} b_j^{\lambda} + (Z_{-j}^{\phi})^{1-\lambda} b_{-j}^{\lambda}},\ \text{where } \lambda = \frac{\alpha(1-\theta)}{\alpha(1-\theta)+1} \tag{8}$$

Combined with (1), we can get an analytical form of the log housing price equation.

To approximate the term associated with the moving probability, we conduct the following linear Taylor approximation to the function $\ln(1+\exp(x))$ at the mean $x = 0$.

$$
\begin{aligned}
&(1-\theta)\ln\left[1+e^{(2\lambda-1)\phi(z_j-z_{-j})+\frac{\theta}{1-\theta}\lambda(\ln\tau_j-\ln\tau_{-j})}\right] \\
&\approx \tfrac{1}{2}\{(1-\theta)(2\lambda-1)\phi(z_j-z_{-j})+\theta\lambda(\ln\tau_j-\ln\tau_{-j})\}+(1-\theta)\ln 2\equiv g_1
\end{aligned}
\tag{9}
$$

In addition, we conduct the quadratic Taylor approximation.

$$
\begin{aligned}
&(1-\theta)\ln\left[1+e^{(2\lambda-1)\phi(z_j-z_{-j})+\frac{\theta}{1-\theta}\lambda(\ln\tau_j-\ln\tau_{-j})}\right] \\
&\approx g_1+\tfrac{1-\theta}{8}\left[\begin{array}{l}\left(\tfrac{\theta}{1-\theta}\right)^2\lambda^2(\ln\tau_j-\ln\tau_{-j})^2+(2\lambda-1)^2\phi^2(z_j-z_{-j})^2 \\ +2(2\lambda-1)\lambda\tfrac{\theta}{1-\theta}\phi(\ln\tau_j-\ln\tau_{-j})(z_j-z_{-j})\end{array}\right]
\end{aligned}
\tag{10}
$$

We confirm numerically that the exact nonlinear function ln(1+exp(x)) and the linear and quadratic approximations (ln(2) + x/2 and ln(2) + x/2 + x^2/8) are close near x = 0. In the relevant domains of the city income z_j and regulation τ_j, the exact nonlinear function has a small curvature, so the approximation works very well in our case (Figure A9).

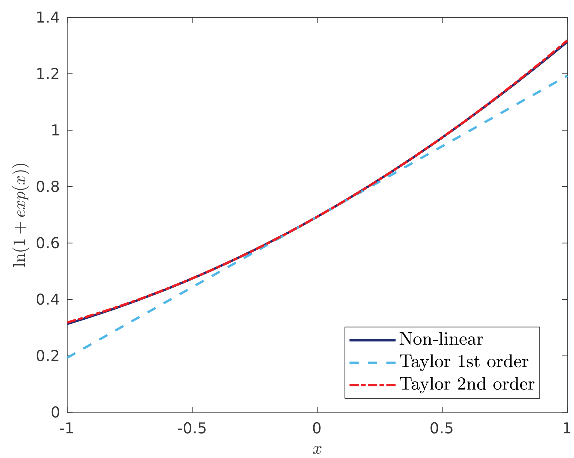


Figure A9: Comparison of ln(1+exp(x)) with the 1st and 2nd order Taylor approximations near x = 0.

For the benchmark model, the empirical log housing price equation based on 2nd order Taylor approximation is as follows.

$$
\begin{aligned}
&\ln p_{ijmt}=\beta_0+f_1+f_2+f_3+f_4+f_5+\varepsilon_{ijmt} \\
&\text{where } f_1=\theta(1-\tfrac{1}{2}\lambda)\cdot CALURI_j+(1-\theta)(\tfrac{3}{2}-\lambda)\phi z_{mt}+\tfrac{1}{2}(1-\theta)(2\lambda-1)\phi z_{0t} \\
&f_2=X_{ijmt}\gamma,\ f_3=N_{jmt}\chi,\ f_4=M_t\nu, \\
&f_5=-\tfrac{1-\theta}{8}\left[\begin{array}{l}\left(\tfrac{\theta}{1-\theta}\lambda\right)^2\cdot CALURI_j^2+(2\lambda-1)^2\phi^2(z_{mt}-z_{0t})^2 \\ +2(2\lambda-1)\lambda\tfrac{\theta}{1-\theta}\cdot CALURI_j\cdot(z_{mt}-z_{0t})\end{array}\right] \\
&z_{0t}=\sum_m g_{mt}z_{mt},\ \sum_m g_{mt}=1,\ \lambda=\tfrac{\alpha(1-\theta)}{\alpha(1-\theta)+1}
\end{aligned}
$$

For the extended model where the supply cost and the income elasticity may depend on per capita income, the empirical price equation based on 2nd order approximation is as follows. The terms with the polynomial order equal or lower than 2 are kept in the equation.

$$
\begin{aligned}
&\ln p_{ijmt} = \beta_0 + f_1 + f_2 + f_3 + f_4 + f_5 + \varepsilon_{ijmt} \\
&\text{where } f_1 = \theta(\delta_0 - \tfrac{1}{2}\lambda)\cdot CALURI_j + \theta\delta_1 z_{mt}\cdot CALURI_j \\
&\qquad + (\tfrac{3}{2}-\lambda)(1-\theta)(\phi_1 z_{mt} + \phi_2 z_{mt}^2) + (\lambda - \tfrac{1}{2})(1-\theta)(\phi_1 z_{0t} + \phi_2 z_{0t}^2) \\
&f_2 = X_{ijmt}\gamma,\ f_3 = N_{jmt}\chi,\ f_4 = M_t \nu \\
&f_5 = -\tfrac{1-\theta}{8}\begin{bmatrix} \left(\tfrac{\theta}{1-\theta}\lambda\delta_0\right)^2 \cdot CALURI_j^2 + (2\lambda-1)^2\phi_1^2 (z_{mt}-z_{0t})^2 \\ +2(2\lambda-1)\delta_0\lambda\tfrac{\theta}{1-\theta}\phi_1 \cdot CALURI_j \cdot (z_{mt}-z_{0t}) \end{bmatrix}
\end{aligned}
$$

We rewrite the equation above to decompose the total effect of regulation up to the 2nd order into the partial equilibrium effect and the general equilibrium effect (with 1st and 2nd order effects).[15]

$$
\begin{aligned}
\ln p_{ijmt} = &\underbrace{-\tfrac{1}{2}\theta\lambda(CALURI_j - CALURI_{-j}) - (\lambda-\tfrac{1}{2})(1-\theta)[\phi_1(z_{mt}-z_{0t}) + \phi_2(z_{mt}^2 - z_{0t}^2)]}_{GE\ Channel\ (1st\ Order)} \\
&\underbrace{-\tfrac{1-\theta}{8}\begin{bmatrix} \left(\tfrac{\theta}{1-\theta}\lambda\delta_0\right)^2 (CALURI_j - CALURI_{-j})^2 + (2\lambda-1)^2\phi_1^2(z_{mt}-z_{0t})^2 \\ +2(2\lambda-1)\phi_1(\tfrac{\theta}{1-\theta}\lambda\delta_0)(CALURI_j - CALURI_{-j})(z_{mt}-z_{0t}) \end{bmatrix}}_{GE\ Channel\ (2nd\ Order)} \\
&+\underbrace{\theta(\delta_0 + \delta_1 z_{mt})CALURI_j}_{PE\ Channel} + (1-\theta)(\phi_1 z_{mt} + \phi_2 z_{mt}^2) + [other\ terms]_{ijmt}
\end{aligned}
\tag{11}
$$

Model 3 imposes the parametric restriction that $\delta_0 = 1$, $\delta_1 = 0$, $\phi_0 = 0$ and $\phi_2 = 0$, and the GE channel for the 2nd order is assumed to be zero which imposes a linear GE effect and no correlation of the GE effect with per capita income.

For Model 4, the GE channel for the 2nd order is assumed to be zero and there is no parametric restriction in Model 3. For the extended Model 4 with the interactive and quadratic effect of the demeaned regulation and demeaned per capita income, we include all terms up to the 2nd order of the log moving probability to establish the correlation of the GE effect and per capita income.

[15] We define the PE and GE effects in this way, because it achieves certain normalization. With regulation and income evaluated at the mean ($CALURI_j = CALURI_{-j} = 0$, $z_{mt} = z_{0t}$), the PE and GE effects have zero values. The complete functional form of the log housing price equation approximated to the 2nd order is given in the appendix.

A.4 Auxiliary Tables and Figures

A.4.1 Estimation Result of Step 1

In Table A5, we report the estimation result of step 1 in which we regress the log housing price on a set of housing characteristics to separate the housing price variation from housing, regional and macro characteristics from regulation and per capita income.

Table A5. Estimation Result of Step 1 in Tables 5

	Without Housing Controls		With Housing Controls	
	β	se	β	se
Bedroom: 1			-0.0273***	(0.003)
Bedroom: 2			-0.212***	(0.003)
Bedroom: 3			-0.300***	(0.003)
Bedroom: 4			-0.365***	(0.003)
Bedroom: 5+			-0.499***	(0.003)
Bathroom: 1			0.0778***	(0.006)
Bathroom: 2			0.202***	(0.006)
Bathroom: 3			0.254***	(0.006)
Bathroom: 4			0.396***	(0.007)
Bathroom: 5+			0.592***	(0.007)
Log Sq.Feet			1.044***	(0.001)
Log Miles to CBD			0.00962***	(0.000)
Log Miles to Pacific Coast			-0.164***	(0.000)
Single-Family			-0.0869***	(0.001)
Condominium			0.0182***	(0.002)
Age: 1-5			0.177***	(0.001)
Age: 6-10			0.0742***	(0.001)
Age: 11-20			0.0672***	(0.001)
Age: 21-30			0.0698***	(0.001)
Age: 31-40			0.135***	(0.001)
Age: 41-50			0.212***	(0.001)
Age: 51-60			0.271***	(0.001)
Age: 61-70			0.304***	(0.002)
Age: > 70			0.339***	(0.002)
No.of Days Good Air Quality	0.00150***	(0.000)	0.000887***	(0.000)
Growth Rate of Mortgage Debt	4.456***	(0.007)	4.468***	(0.006)
30-year FRM Rate	-18.58***	(0.028)	-17.52***	(0.022)
Constant	13.23***	(0.002)	5.951***	(0.012)
Adjusted R^2	0.109		0.465	
N	5,285,205		5,285,205	

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. The table reports the results of step 1 in the estimation of the empirical housing price equation. The dependent variable is the log real housing price. The base levels of the factor variables (omitted in table) are: no bedroom, no bathroom, property use other than single-family or condo, new property (property age is zero). The estimation is based on housing transactions from 1993 to 2017 in California.

A.4.2 Model Estimation with Metro-Specific Neighboring Regulation

In Table A6a (A6b), we test whether our estimation results of Models 1 to 5 for 1993-2017 (2012-2017) are robust to the assumption of identical outside moving option by directly controlling the MSA average regulation to measure the outside regulation of a city in equation (13). We report quantitatively similar results which are not driven by the assumption of constant neighboring regulation.

Table A6a. Estimation of Linear and Non-linear Models with Metro-Specific Neighboring Regulation: Parameters and Marginal Effects (1993-2017)

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
θ	0.0247***	0.0249***	0.0246***	0.0347***	0.0258***
	(0.009)	(0.009)	(0.009)	(0.007)	(0.008)
ϕ_1	0.383***	0.379***	0.383***	-8.187***	-1.608
	(0.026)	(0.026)	(0.026)	(1.489)	(2.218)
ϕ_2				1.116***	0.257
				(0.194)	(0.280)

δ_0				-10.787***	-4.058
				(3.982)	(4.231)
δ_1				2.992***	1.284
				(1.011)	(1.074)
Marginal Effect	Model 1	Model 2	Model 3	Model 4	Model 5
CALURI	0.0247***	0.0249***	0.0246***	-0.374***	-0.105
	(0.009)	(0.009)	(0.009)	(0.122)	(0.116)
CALURI – $CALURI_m$	-0.00202***	-0.00203***	-0.00201***	-0.00281***	-0.00210***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Income Per Capita	0.500***	0.494***	0.499***	-10.58***	-2.095
	(0.034)	(0.033)	(0.033)	(1.919)	(2.891)
Avg. Log Income Per Capita	-0.126***	-0.125***	-0.126***	2.673***	0.528
	(0.009)	(0.008)	(0.008)	(0.485)	(0.728)
CALURI*Log Income Per Capita				0.104***	0.0331
				(0.031)	(0.030)
Sq. Log Income Per Capita				1.441***	0.334
				(0.250)	(0.365)
Sq. Avg. Log Income Per Capita				-0.364***	-0.0842
				(0.063)	(0.092)
Sq. Demeaned Log Income					-0.143
Per Capita					(0.395)
Demeaned Log Income Per Capita					0.00462
*Demeaned CALURI					(0.007)
Sq. Demeaned CALURI					-0.0000374
					(0.000)
Observations	4620	4620	4620	4620	4620

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. A linear model is used to separate housing price variations due to housing, regional and macro controls in step 1, while GMM is used to estimate the model parameters in step 2. The estimation in step 1 is based on housing transactions from 1993 to 2017 in California. The controls used in step 1 include 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 days with good air quality. $CALURI_m$ refers to the neighboring regulation of a city and is defined as the average regulation of an MSA where a city is located.

Table A6b. Estimation of Linear and Non-linear Models with Metro-Specific Neighboring Regulation: Parameters and Marginal Effects (2012-2017)

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
θ	0.0661***	0.0667***	0.0661***	0.0737***	0.0652***
	(0.011)	(0.011)	(0.009)	(0.008)	(0.008)
ϕ_1	0.442***	0.429***	0.463***	-9.126***	-1.411
	(0.046)	(0.046)	(0.042)	(1.275)	(15.956)
ϕ_2				1.214***	0.237
				(0.160)	(1.963)
δ_0				-6.765***	-1.940
				(2.529)	(2.801)
δ_1				1.907***	0.722
				(0.621)	(0.688)
Marginal Effect	Model 1	Model 2	Model 3	Model 4	Model 5
CALURI	0.0661***	0.0667***	0.0661***	-0.499***	-0.126
	(0.011)	(0.011)	(0.009)	(0.165)	(0.184)
CALURI – $CALURI_m$	-0.00520***	-0.00524***	-0.00520***	-0.00576***	-0.00513***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Income Per Capita	0.554***	0.538***	0.580***	-11.36***	-1.771
	(0.058)	(0.058)	(0.053)	(1.566)	(20.029)
Avg. Log Income Per Capita	-0.141***	-0.137***	-0.148***	2.905***	0.452
	(0.015)	(0.015)	(0.013)	(0.402)	(5.109)
CALURI*Log Income Per Capita				0.141***	0.0470
				(0.040)	(0.045)
Sq. Log Income Per Capita				1.511***	0.298
				(0.196)	(2.464)
Sq. Avg. Log Income Per Capita				-0.387***	-0.0759
				(0.050)	(0.628)
Sq. Demeaned Log Income					-0.109
Per Capita					(2.470)
Demeaned Log Income Per Capita					0.00481
*Demeaned CALURI					(0.050)
Sq. Demeaned CALURI					-0.0000530
					(0.000)
Observations	1,144	1,144	1,144	1,144	1,144

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. A linear model is used to separate housing price variations due to housing, regional and macro controls in step 1, while GMM is used to estimate the model parameters in step 2. The estimation in step 1 is based on housing transactions from 2012 to 2017 in California. The controls used in step 1 include 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 days with good air quality. $CALURI_m$ refers to the neighboring regulation of a city and is defined as the average regulation of an MSA where a city is located.

A.4.3 Housing Prices Response to +1 SD CALURI by MSA and Historical Estimates

In Table A7, we replicate Table 7 but use the historical estimates to decompose the PE and GE effects based on Models 3-5. In Table A8, we replicate Table 8 but use the historical estimates to decompose the housing prices responses in the case of regulation relaxation to the MSA mean or minimum level for the selected cities.

Table A7. Housing Price Responses (%) to +1 SD CALURI by MSA (1993-2017)

	Model 3 Constant Effect with Constant Neighboring Regulation			Model 4 Linear Approx. with Constant Neighboring Regulation			Model 5 Quadratic Approx. with Constant Neighboring Regulation			Model 5 Quadratic Approx. with MSA-Specific Neighboring Regulation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MSA	PE	GE	TE	PE	GE	TE	PE	GE	TE	PE	GE	TE
Bakersfield, CA	3.60	-0.29	3.31	2.30	-0.31	1.99	2.81	-0.35	2.47	1.96	-0.30	1.66
Chico, CA	3.60	-0.29	3.31	2.37	-0.31	2.06	2.84	-0.37	2.47	1.99	-0.32	1.67
Fresno, CA	3.60	-0.29	3.31	2.26	-0.31	1.95	2.80	-0.36	2.44	1.94	-0.31	1.63
Hanford-Corcoran, CA	3.60	-0.29	3.31	-1.04	-0.31	-1.35	1.59	-0.53	1.07	0.58	-0.50	0.08
Los Angeles-Long Beach-Anaheim, CA	3.60	-0.29	3.31	4.42	-0.31	4.11	3.59	-0.24	3.35	2.83	-0.17	2.66
Madera, CA	3.60	-0.29	3.31	-0.33	-0.31	-0.64	1.85	-0.51	1.35	0.88	-0.48	0.40
Merced, CA	3.60	-0.29	3.31	-0.74	-0.31	-1.04	1.70	-0.52	1.18	0.71	-0.50	0.21
Modesto, CA	3.60	-0.29	3.31	1.02	-0.31	0.72	2.35	-0.41	1.94	1.43	-0.37	1.07
Napa, CA	3.60	-0.29	3.31	3.91	-0.31	3.60	3.40	-0.27	3.14	2.62	-0.20	2.42
Oxnard-Thousand Oaks-Ventura, CA	3.60	-0.29	3.31	2.46	-0.31	2.15	2.87	-0.34	2.53	2.02	-0.29	1.74
Redding, CA	3.60	-0.29	3.31	3.36	-0.31	3.06	3.21	-0.31	2.89	2.40	-0.26	2.14
Riverside-San Bernardino-Ontario, CA	3.60	-0.29	3.31	0.67	-0.31	0.36	2.22	-0.43	1.79	1.29	-0.39	0.90
Sacramento-Roseville, CA	3.60	-0.29	3.31	4.06	-0.31	3.75	3.46	-0.26	3.20	2.68	-0.19	2.49
Salinas, CA	3.60	-0.29	3.31	2.05	-0.31	1.75	2.73	-0.36	2.37	1.86	-0.31	1.55
San Diego-Carlsbad, CA	3.60	-0.29	3.31	4.11	-0.31	3.80	3.48	-0.25	3.22	2.71	-0.19	2.52
San Francisco-Oakland-Hayward, CA	3.60	-0.29	3.31	5.50	-0.31	5.19	3.99	-0.18	3.80	3.28	-0.11	3.17
San Jose-Sunnyvale-Santa Clara, CA	3.60	-0.29	3.31	5.49	-0.31	5.18	3.98	-0.18	3.80	3.27	-0.11	3.17
San Luis Obispo-Paso Robles, CA	3.60	-0.29	3.31	3.40	-0.31	3.09	3.22	-0.29	2.92	2.41	-0.23	2.18
Santa Cruz-Watsonville, CA	3.60	-0.29	3.31	2.67	-0.31	2.36	2.95	-0.33	2.62	2.11	-0.27	1.84
Santa Maria-Santa Barbara, CA	3.60	-0.29	3.31	3.67	-0.31	3.36	3.32	-0.28	3.04	2.52	-0.21	2.31
Santa Rosa, CA	3.60	-0.29	3.31	3.02	-0.31	2.71	3.08	-0.31	2.77	2.26	-0.26	2.00
Stockton-Lodi, CA	3.60	-0.29	3.31	1.12	-0.31	0.81	2.38	-0.41	1.97	1.47	-0.37	1.11
Vallejo-Fairfield, CA	3.60	-0.29	3.31	1.21	-0.31	0.90	2.42	-0.40	2.01	1.51	-0.36	1.15
Visalia-Porterville, CA	3.60	-0.29	3.31	-0.26	-0.31	-0.57	1.88	-0.47	1.41	0.90	-0.44	0.46
Yuba City, CA	3.60	-0.29	3.31	0.08	-0.31	-0.23	2.00	-0.49	1.51	1.04	-0.47	0.58

Note: percentage deviation (%) of MSA housing prices to +1 SD of CALURI. The total effect (TE) is decomposed into the partial equilibrium effect (PE) and the general equilibrium effect (GE). *Constant Effect* is based on Model 3 in Table 5. *Linear Approximation* and *Quadratic Approximation* indicate the type of method to approximate the log moving probability in the estimation of the housing price equation of Models 4 and 5 in Table 5. The estimation is based on housing transactions from 1993 to 2017 in California. The quadratic specification uses the average per capita income from 1993 to 2017 to derive the PE and GE effects. Models 3 and 4 assumes constant neighboring regulation (average regulation in California), while Model 5 assumes the neighboring regulation of a city to be the average regulation of the MSA where a city is located.

Table A8. Counterfactual Price Changes (%) in Response to Relaxing Regulation (1993-2017)

City CALURI	Los Angeles City (3.38)		San Francisco City (1.04)		San Diego City (0.30)	
Scenario	MSA Mean (-0.20)	MSA Min (-1.89)	MSA Mean (-0.22)	MSA Min (-3.23)	MSA Mean (-0.25)	MSA Min (-1.04)
PE (%)	-13.98	-20.60	-5.34	-18.13	-2.17	-5.21
GE (%)	0.89	1.29	0.25	0.81	0.14	0.32
TE (%)	-13.09	-19.31	-5.09	-17.32	-2.03	-4.89

Note: the experiment considers relaxing city regulation to the MSA mean or minimum regulatory level. The price change attributed to the partial equilibrium (PE) is defined as the difference of the PE effect in the counterfactual case with the relaxed regulatory level and the PE effect without regulatory change. The price change attributed to the general equilibrium (GE) effect is defined in a similar way. The total price change (TE) is the sum of the price change attributed to PE and GE effects. The estimation is based on housing transactions from 1993 to 2017 in California. The model specification is based on Model 4 in Table 5 with the quadratic-approximated log moving probability and uses the average per capita income from 1993 to 2017 to derive the PE and GE effects.

A.4.4 Time-varying Regulatory Impact

In Table A9, we report the marginal effect of regulation estimated based on a 3-year moving bandwidth. We decompose the total effect into the PE and GE effect and calculate the ratio of GE to PE effects as a relative regulatory measure. Figure 8 in the main paper uses the estimates over time in this table.

Table A9. Estimations of Model 3 in Table 5 by 3-Year moving bandwidth

Initial	CALURI		PE Effect		GE Effect		Ratio of GE to PE		N
Year	β	se	β	se	β	se	β	se	
1995	0.00433	(0.00811)	0.00472	(0.00884)	-0.000392	(0.000731)	-0.0830***	(0.000615)	515
1996	0.0119	(0.00792)	0.0130	(0.00863)	-0.00107	(0.000703)	-0.0824***	(0.000602)	528
1997	0.0183**	(0.00840)	0.0199**	(0.00913)	-0.00163**	(0.000736)	-0.0819***	(0.000638)	542
1998	0.0147	(0.0155)	0.0160	(0.0169)	-0.00132	(0.00137)	-0.0822***	(0.00118)	549
1999	0.0201	(0.0131)	0.0218	(0.0142)	-0.00179	(0.00114)	-0.0818***	(0.000993)	554
2000	0.0249*	(0.0133)	0.0271*	(0.0145)	-0.00221*	(0.00115)	-0.0814***	(0.00102)	555
2001	0.0297***	(0.00844)	0.0323***	(0.00916)	-0.00262***	(0.000722)	-0.0811***	(0.000643)	561
2002	0.0215*	(0.0124)	0.0234*	(0.0135)	-0.00191*	(0.00108)	-0.0817***	(0.000942)	567
2003	0.0175	(0.0191)	0.0191	(0.0208)	-0.00156	(0.00168)	-0.0820***	(0.00146)	574
2004	0.0156	(0.0188)	0.0170	(0.0204)	-0.00140	(0.00165)	-0.0821***	(0.00143)	572
2005	0.0228	(0.0199)	0.0249	(0.0216)	-0.00203	(0.00173)	-0.0816***	(0.00151)	569
2006	0.0527***	(0.0144)	0.0573***	(0.0155)	-0.00454***	(0.00117)	-0.0793***	(0.00110)	567
2007	0.0485**	(0.0215)	0.0527**	(0.0233)	-0.00419**	(0.00177)	-0.0796***	(0.00164)	566
2008	0.0491***	(0.0155)	0.0534***	(0.0168)	-0.00425***	(0.00127)	-0.0796***	(0.00119)	567
2009	0.0470***	(0.0106)	0.0511***	(0.0115)	-0.00407***	(0.000874)	-0.0798***	(0.000811)	568
2010	0.0536***	(0.0138)	0.0582***	(0.0149)	-0.00462***	(0.00112)	-0.0792***	(0.00106)	570
2011	0.0549***	(0.0142)	0.0596***	(0.0153)	-0.00472***	(0.00115)	-0.0792***	(0.00109)	573
2012	0.0641***	(0.0181)	0.0696***	(0.0195)	-0.00546***	(0.00144)	-0.0784***	(0.00139)	576
2013	0.0698***	(0.00818)	0.0757***	(0.00882)	-0.00591***	(0.000640)	-0.0780***	(0.000628)	576
2014	0.0760***	(0.00886)	0.0824***	(0.00954)	-0.00639***	(0.000684)	-0.0775***	(0.000681)	575
2015	0.0823***	(0.00981)	0.0892***	(0.0106)	-0.00687***	(0.000746)	-0.0770***	(0.000755)	568

Note: robust standard errors in *se* columns. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. Column *β* reports the marginal effect and Column *se* reports the standard error. Column *Initial Year* indicates the initial year of the 3-year moving bandwidth (e.g. year 2015 indicates 2015-2017). The specification is based on Model 3 in Table 5.

To show the model predictions for local housing price outcomes, we aggregate the estimated and actual housing prices using the 6 most populated MSAs in California.[16] The central cities of these MSAs are Los Angeles, San Francisco, Riverside, San Diego, San Jose and Fresno. Figure A9 compares actual and estimated prices based on the estimates of Model 4 in Table 5. Considering that we don't introduce location or time dummies to absorb cross-sectional or time-series variation but model their price impacts directly, the estimated prices in our empirical model based on a small set of parameters trace the actual prices quite closely.

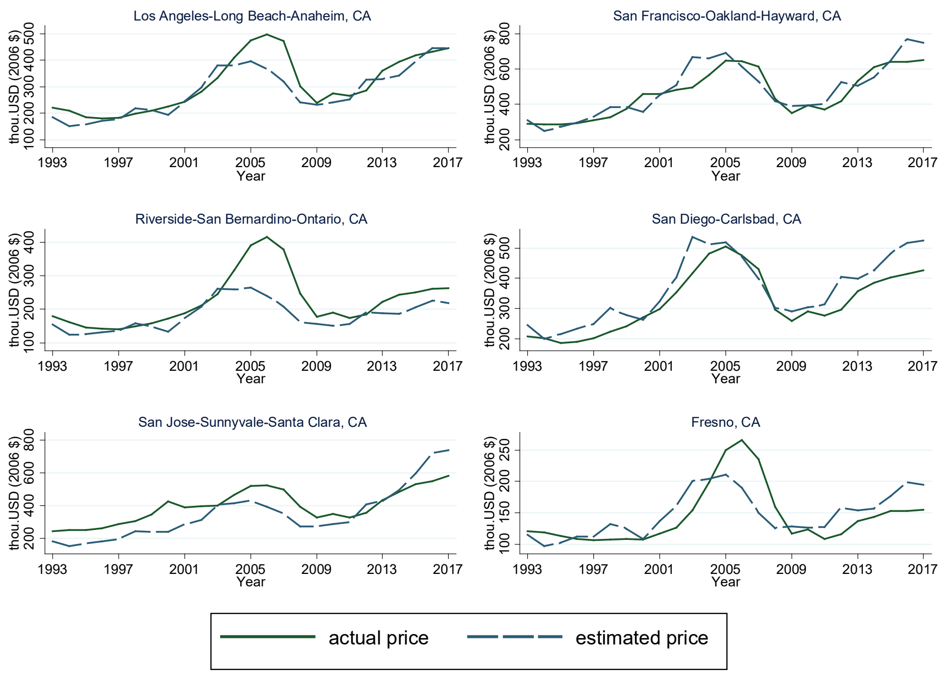


Figure A9: housing price dynamics of 6 MSAs in California: actual price vs estimated price. The structural estimation is based on Model 4 in Table 5. The subplots are sorted by the MSA population in 2006 in descending order. The prices are geometrically averaged by year and MSA.

In Table A10, we report the full estimation results of the specifications about neighboring regulation in Table 9. In Table A11, we report the full estimation results of the specifications about city per capita income in Table 10.

[16] 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.

Table A10. Log Housing Price and Regulatory Impacts in Greater Los Angeles (Complete Table)

	(1)	(2)	(3)	(4)	(5)	(6)
	Model 3	Model 3	Model 3	Model 3	Model 3	Model 3
CALURI	0.0670***	0.111***	0.162***	0.192***	-0.00385	-0.00932
	(0.001)	(0.002)	(0.007)	(0.008)	(0.003)	(0.011)
Log Income Per Capita	-1.576***	-2.933***	-1.335***	-2.691***	-1.981***	-1.999***
	(0.100)	(0.105)	(0.101)	(0.106)	(0.102)	(0.104)
Log Income Per Capita Squared	0.355***	0.552***	0.315***	0.513***	0.413***	0.416***
	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
Single-Family	0.0893***	0.0808***	0.0801***	0.0731***	0.0976***	0.0985***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Condominium	0.000915	-0.0321***	-0.0106	-0.0412***	-0.00303	-0.00208
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.012)
Bedroom: 1	-0.0226	-0.0156	-0.0198	-0.0133	-0.0114	-0.0116
	(0.035)	(0.034)	(0.035)	(0.034)	(0.035)	(0.035)
Bedroom: 2	-0.127***	-0.121***	-0.121***	-0.116***	-0.109***	-0.110***
	(0.034)	(0.033)	(0.034)	(0.032)	(0.033)	(0.033)
Bedroom: 3	-0.231***	-0.200***	-0.219***	-0.191***	-0.199***	-0.200***
	(0.034)	(0.033)	(0.034)	(0.033)	(0.033)	(0.033)
Bedroom: 4+	-0.378***	-0.331***	-0.362***	-0.318***	-0.340***	-0.341***
	(0.034)	(0.033)	(0.034)	(0.033)	(0.034)	(0.034)
Bathroom: 1	0.284**	0.285**	0.284**	0.285**	0.275**	0.275**
	(0.123)	(0.121)	(0.123)	(0.121)	(0.125)	(0.125)
Bathroom: 2	0.343***	0.350***	0.341***	0.348***	0.336***	0.336***
	(0.123)	(0.121)	(0.123)	(0.121)	(0.125)	(0.125)
Bathroom: 3	0.388***	0.370***	0.382***	0.366***	0.366***	0.366***
	(0.123)	(0.122)	(0.123)	(0.122)	(0.125)	(0.125)
Bathroom: 4+	0.634***	0.599***	0.623***	0.590***	0.596***	0.597***
	(0.124)	(0.122)	(0.124)	(0.122)	(0.125)	(0.125)
Log Sq.Feet	0.949***	0.940***	0.944***	0.936***	0.943***	0.943***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Log Miles to CBD	-0.107***	-0.0934***	-0.106***	-0.0929***	-0.107***	-0.107***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age: 1-5	0.0216	0.0245	0.0143	0.0181	0.0233	0.0236
	(0.027)	(0.025)	(0.026)	(0.025)	(0.028)	(0.028)
Age: 6-10	-0.0823***	-0.0872***	-0.0938***	-0.0969***	-0.108***	-0.108***
	(0.027)	(0.024)	(0.026)	(0.024)	(0.027)	(0.027)
Age: 11-20	-0.101***	-0.0958***	-0.111***	-0.105***	-0.119***	-0.119***
	(0.026)	(0.024)	(0.025)	(0.023)	(0.027)	(0.027)
Age: 21-30	-0.119***	-0.115***	-0.135***	-0.129***	-0.155***	-0.155***
	(0.026)	(0.023)	(0.025)	(0.023)	(0.026)	(0.026)
Age: 31-40	-0.0889***	-0.0912***	-0.106***	-0.106***	-0.128***	-0.127***
	(0.026)	(0.023)	(0.025)	(0.023)	(0.026)	(0.026)
Age: 41-50	0.0257	0.0229	0.00619	0.00626	-0.0203	-0.0198
	(0.026)	(0.024)	(0.025)	(0.024)	(0.027)	(0.027)
Age: > 50	0.160***	0.132***	0.135***	0.111***	0.107***	0.108***
	(0.026)	(0.024)	(0.025)	(0.024)	(0.027)	(0.027)
Log Miles to Pacific Coast	-0.0432***	-0.0634***	-0.0483***	-0.0673***	-0.0564***	-0.0564***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
RRI			0.0964***	0.0827***		-0.00517
			(0.007)	(0.007)		(0.010)
Has high Outside CALURI					0.0961***	0.0987***
					(0.005)	(0.007)
CALURI * Has high Outside CALURI					0.0706***	0.0706***
					(0.003)	(0.003)
Constant					8.152***	8.177***
					(0.250)	(0.253)
Endo. Regulation	No	No	Yes	Yes	No	No
Adjusted R^2	0.563	0.556	0.565	0.558	0.569	0.569
N	61,263	61,263	61,263	61,263	60,135	60,135

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 sample is the property sales in Los Angeles, Orange and Ventura counties in 2016. *Has High Neighboring CALURI* is a binary variable indicating cities whose neighboring regulation is larger than 75th percentile. *Endo. Regulation* indicates whether CALURI (and RRI) is endogenized using political preference. The voting share for Republicans in the 2004 US Presidential Election is used as the instrument to endogenize regulation.

Table A11. Log Housing Price in Los Angeles MSAs by Per Capita Income

	(1)	(2)	(3)	(4)	(5)	(6)
	Model 3	Model 3	Model 3	Model 3	Model 3	Model 3
CALURI	0.0154***	0.0395***	0.150***	0.141***	0.149***	0.172***
	(0.002)	(0.006)	(0.012)	(0.015)	(0.009)	(0.011)
Log Income Per Capita	-15.66***	-4.797***	-15.73***	-0.634	-15.73***	-15.74***
	(0.460)	(0.668)	(0.454)	(0.821)	(0.441)	(0.437)
Log Income Per Capita Squared	2.761***	0.774***	2.766***	0.208*	2.766***	2.766***
	(0.078)	(0.089)	(0.077)	(0.110)	(0.075)	(0.074)
Single-Family	-0.0615***	0.188***	-0.0649***	0.137***	0.0299**	0.0341***
	(0.019)	(0.015)	(0.019)	(0.016)	(0.013)	(0.013)
Condominium	-0.118***	-0.00966	-0.128***	-0.0613***	-0.0742***	-0.0708***
	(0.019)	(0.017)	(0.019)	(0.018)	(0.014)	(0.014)
Bedroom: 1	0.0237	-1.680*	0.0239	-1.668*	-0.0138	-0.0132
	(0.032)	(0.890)	(0.032)	(0.875)	(0.036)	(0.036)
Bedroom: 2	-0.0614*	-1.668*	-0.0596*	-1.648*	-0.0939***	-0.0934***
	(0.032)	(0.888)	(0.032)	(0.872)	(0.035)	(0.035)
Bedroom: 3	-0.163***	-1.700*	-0.158***	-1.674*	-0.177***	-0.177***
	(0.033)	(0.885)	(0.033)	(0.869)	(0.035)	(0.035)
Bedroom: 4+	-0.305***	-1.772**	-0.297***	-1.744**	-0.300***	-0.299***
	(0.034)	(0.882)	(0.034)	(0.866)	(0.035)	(0.035)
Bathroom: 1	0.294*	1.976	0.293*	1.936	0.326*	0.326*
	(0.169)	(1.314)	(0.169)	(1.304)	(0.176)	(0.175)
Bathroom: 2	0.369**	1.954	0.369**	1.911	0.398**	0.399**
	(0.169)	(1.319)	(0.169)	(1.309)	(0.176)	(0.176)
Bathroom: 3	0.395**	1.946	0.393**	1.911	0.422**	0.421**
	(0.169)	(1.322)	(0.169)	(1.313)	(0.176)	(0.176)
Bathroom: 4+	0.700***	2.122	0.693***	2.088	0.659***	0.658***
	(0.170)	(1.327)	(0.170)	(1.317)	(0.177)	(0.177)
Log Sq.Feet	0.998***	0.835***	0.997***	0.820***	0.951***	0.952***
	(0.013)	(0.032)	(0.013)	(0.032)	(0.018)	(0.018)
Log Miles to CBD	-0.139***	-0.0812***	-0.140***	-0.0864***	-0.126***	-0.126***
	(0.003)	(0.008)	(0.003)	(0.008)	(0.003)	(0.003)
Age: 1-5	-0.00719	0.0674***	-0.0259	0.0621**	-0.0551*	-0.0578**
	(0.036)	(0.026)	(0.033)	(0.028)	(0.029)	(0.029)
Age: 6-10	-0.122***	0.00433	-0.142***	-0.00136	-0.140***	-0.143***
	(0.032)	(0.029)	(0.030)	(0.031)	(0.029)	(0.029)
Age: 11-20	-0.139***	-0.0214	-0.157***	-0.0321	-0.156***	-0.158***
	(0.032)	(0.026)	(0.029)	(0.028)	(0.028)	(0.028)
Age: 21-30	-0.162***	-0.0604**	-0.181***	-0.0762***	-0.193***	-0.195***
	(0.031)	(0.025)	(0.029)	(0.028)	(0.028)	(0.028)
Age: 31-40	-0.146***	-0.0631**	-0.166***	-0.0711**	-0.170***	-0.173***
	(0.031)	(0.026)	(0.029)	(0.028)	(0.028)	(0.028)
Age: 41-50	0.00550	-0.0524**	-0.0122	-0.0639**	-0.0625**	-0.0653**
	(0.031)	(0.024)	(0.029)	(0.027)	(0.028)	(0.028)
Age: > 50	0.113***	0.0842***	0.0877***	0.0702**	0.0446	0.0412
	(0.031)	(0.025)	(0.029)	(0.028)	(0.028)	(0.028)
Log Miles to Pacific Coast	-0.0291***	-0.0706***	-0.0346***	-0.0755***	-0.0529***	-0.0532***
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.002)
RRI			0.133***	0.105***	0.126***	0.150***
			(0.011)	(0.014)	(0.009)	(0.011)
Has High Income					-30.07***	-28.18***
					(1.426)	(1.517)
CALURI * Has High Income					0.000349	
					(0.005)	
Log Per Capita Income * Has High Income					19.42***	18.38***
					(0.819)	(0.868)
Log Per Capita Income Sq. * Has High Income					-3.147***	-3.005***
					(0.120)	(0.126)
RRI * Has High Income						-0.0491***
						(0.018)
Constant	27.72***	14.23***	27.95***	6.837***	28.23***	28.24***
	(0.702)	(1.622)	(0.696)	(1.824)	(0.686)	(0.681)
Adjusted R^2	0.519	0.680	0.520	0.682	0.602	0.602
N	39,345	13,945	39,345	13,945	53,290	53,290

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 sample is the property sales in Los Angeles and Orange counties in 2016. *Has High Income* is an indicator that cities has per capita income above the median in the Los Angeles MSA.

A.5 Additional Results

A.5.1 Additional Model Specifications

We consider model specifications alternative to Model 1 in Table 5, and report the estimation results in Table A12. First, we consider the specification without housing characteristics. Compared to Model 1, the estimates of θ and ϕ are very much biased upward in Model 1 without housing controls, leading to an overestimated marginal effect of income and an estimate of income elasticity of housing demand inconsistent with the literature.[17]

Second, we examine whether using a more precise 2nd order approximation of the log moving probability in the log price equation improves the estimates of the average marginal effects. The functional form of the 2nd order approximated log price equation is available in appendix section A2. We find that when our focus is the average marginal effects, the estimated coefficients and marginal effects with more previse approximation is not statistically different from those in Model 1. Hence, we pursue the simpler specification of Model 1 in the main paper.

Table A12a. Alternative Specifications: Parameters and Marginal Effect (1993-2017)

Parameter	No Housing Controls	2nd Order Approximation	Model 1
θ	0.0393***	0.0293***	0.0293***
	(0.009)	(0.009)	(0.009)
ϕ	0.820***	0.429***	0.429***
	(0.033)	(0.027)	(0.027)
Marginal Effect	No Housing Controls	2nd Order Approximation	Model 1
CALURI	0.0361***	0.0269***	0.0269***
	(0.008)	(0.008)	(0.008)
Log Income Per Capita	1.054***	0.557***	0.557***
	(0.041)	(0.034)	(0.034)
Avg. Log Income Per Capita	-0.267***	-0.140***	-0.140***
	(0.010)	(0.009)	(0.009)
Housing Controls	No	Yes	Yes
N	4,620	4,620	4,620

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. A linear model is used to separate housing price variations due to housing, regional and macro controls in step 1, while GMM is used to estimate the model parameters in step 2. The estimation in step 1 is based on housing transactions from 1993 to 2017 in California. The controls used in step 1 include 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 days with good air quality. *Housing* indicates whether housing characteristics are controlled in step 1.

[17] The income elasticity in the specification without housing controls is more than 0.8, more than double the estimate in the literature. The number of bedrooms/bathrooms and property size are negatively correlated with regulation, leading to the biased estimates.

Table A12b. Alternative Specifications: Parameters and Marginal Effect (2012-2017)

Parameter	No Housing Controls	2nd Order Approximation	Model 1
θ	0.0934***	0.0652***	0.0654***
	(0.012)	(0.010)	(0.010)
ϕ	1.008***	0.454***	0.456***
	(0.064)	(0.043)	(0.043)
Marginal Effect	No Housing Controls	2nd Order Approximation	Model 1
CALURI	0.0863***	0.0601***	0.0602***
	(0.011)	(0.009)	(0.009)
Log Income Per Capita	1.231***	0.570***	0.572***
	(0.077)	(0.055)	(0.055)
Avg. Log Income Per Capita	-0.317***	-0.145***	-0.146***
	(0.020)	(0.014)	(0.014)
Housing	No	Yes	Yes
N	1,144	1,144	1,144

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. A linear model is used to separate housing price variations due to housing, regional and macro controls in step 1, while GMM is used to estimate the model parameters in step 2. The estimation in step 1 is based on housing transactions from 2012 to 2017 in California. The controls used in step 1 include 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 days with good air quality. *Housing* indicates whether housing characteristics are controlled in step 1.

In Table A13, we compare Models 1 and 3 in Table 5 for the 1993-2017 sample with the their reduced-from counterparts. The reduced-form models are unconstrained in the marginal effects.

Table A13. Comparison of Structural and Reduced Form Estimates

	Model 1	Model 1'	Model 3	Model 3'
CALURI	0.0269***	0.0242***	0.0331***	0.0242***
	(0.008)	(0.005)	(0.008)	(0.005)
Log Income Per Capita	0.557***	0.766***	0.511***	0.769***
	(0.034)	(0.025)	(0.033)	(0.025)
Avg. Log Income Per	-0.140***	-0.355***	-0.129***	-0.312***
Capita	(0.009)	(0.044)	(0.008)	(0.045)
Estimator	GMM	OLS	GMM-IV	2SLS
Structural	Yes	No	Yes	No
N	4,620	4,620	4,620	4,620

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Models 1 and 3 comes from Table 5. Models 1' and 3' ignore the parametric restrictions and estimate the coefficients in reduced from.

We replicate the estimations in Table 5 for the 1993-2017 sample but instead use WRLURI as our regulatory measure. Compared with Table 5, the marginal effect of regulation in Table A14 is larger, while the marginal effect of per capita income based on WRLURI is smaller.[18]

[18] There are two sources of underestimating the regulatory impact using CALURI. The first is due to the larger standard deviation of CALURI than WRLURI (Table 2). If we scale down a regulatory index (e.g. CALURI) by multiplying a factor $x < 1$, we will scale up the regulatory impact by a factor of $1/x > 1$ in estimation. The second source is about the non-linear relationship between CALURI and WRLURI.

Table A14. Benchmark Estimation: Parameters and Marginal Effects (1993-2017; WRLURI)

Parameter	Model 1	Model 2	Model 3
θ	0.0318**	0.0321**	0.0392***
	(0.013)	(0.014)	(0.013)
ϕ	0.419***	0.411***	0.388***
	(0.027)	(0.026)	(0.026)
Marginal Effect	Model 1	Model 2	Model 3
WRLURI	0.0292**	0.0295**	0.0360***
	(0.012)	(0.012)	(0.012)
Log Income Per Capita	0.542***	0.532***	0.499***
	(0.034)	(0.033)	(0.033)
Avg. Log Income Per Capita	-0.137***	-0.134***	-0.126***
	(0.009)	(0.008)	(0.008)
Endogenize	No	Income (1)	Income (4)
Instrument	NA	Lag	Lag & Demo
N	4,620	4,620	4,620

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. *Endogenize* indicates whether income or regulation is treated as endogenous. The number of instruments is listed in the parenthesis. The instruments used to endogenize a variable are listed under *Instrument*. *Demo* includes share of high education, population age, and share of high-tech jobs.

A.5.2 Tests of Instrument Validity

We report the p-values of the Sargan-Hansen's J test of exclusive restrictions for models in Table 5 for 1993-2017 and 2012-2017 samples. A larger p-value indicates that the null hypothesis that the over-identifying restrictions are valid is accepted. In Table A15, we show that the p-values of all models for historical and recent estimates are larger than 5%, suggesting that the null hypothesis is accepted.

Table A15. Sargan-Hansen J Test (Table 5)

	Model 1	Model 2	Model 3	Model 4
Degree of Freedom	1	1	4	4
1993-2017 Sample	0.209	0.124	0.090	0.108
2012-2017 Sample	0.269	0.241	0.112	0.143

Note: the table reports the p-values of the instrument validity tests of Table 5.

A.5.3 Endogenous Regulation

The top 3 factors underlying CALURI (Local political pressure, local project approval and local zoning approval) are associated with political environment and explain more 60% in CALURI. This motivates us to use political preference to endogenize regulation. We aggregate the precinct-level data from the Harvard Election Data Archive to use the log odds ratio of the city-level voting share for the Republican party in the presidential election as the instrument, so both CALURI and its instrument have the same domain on the real line. The election data in 2004 is from Harvard Election Data Archive and the data in 2016 is from MIT Election Data and Science Lab. We report the test results of exogenous validity and show that those instruments pass the Sargan-Hansen's J tests at 5% level. Quigley et al (2008) similarly consider using political preference to endogenize regulation in study of the San Francisco Bay Area. In Figure A10, we plot the political preference in 2004 and 2016 against CALURI at the city level.

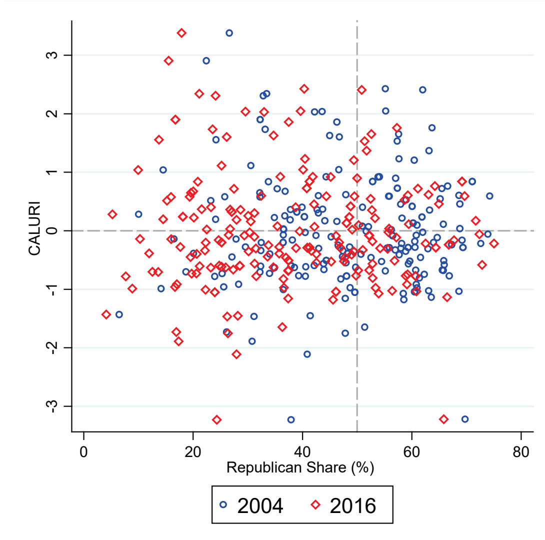


Figure A10: Relationship between land use regulation and political preference. Political preference is defined as the voting share (%) for the Republican party in the US presidential elections (2004, 2016).

In Table A16a (A16b), we compare the specifications with endogenous regulation based on the 1993-2017 (2012-2017) sample to Model 1 in Table 5 where regulation and per capita income are exogenous. The results about endogenizing regulation are mixed. The model using political preference in 2004 doesn't find a significant marginal effect of regulation for 1993-2017 but find a smaller effect than Model 5 for 2012-2017, while the Model using political preference in 2016 finds a larger regulatory effect on housing prices for both sample periods. The mixed result may be associated with weak instrumental variables. As Figure A10 shows, the correlation between political preference and CALURI is not different not significant and remains insignificant when per capita income is controlled. Large measurement errors in the regulation survey may be responsible for the weak instrumental variable issue. As the estimated effects with endogenous regulation are subject to potential biases, we will proceed under the assumption of exogenous regulation in the main paper. In Table A16c, we report the Sargan-Hansen's J tests of models in Table 16a and A16b. We show that the instruments pass the validity test at 5% level.

Table A16a. Benchmark and Endogenous Regulation: Parameters and Marginal Effects (1993-2017)

Parameter	2004 Political Preference	2016 Political Preference	Model 1
θ	0.0142	0.0495***	0.0293***
	(0.017)	(0.017)	(0.009)
ϕ	0.414***	0.431***	0.429***
	(0.028)	(0.028)	(0.027)
Marginal Effect	2004 Political Preference	2016 Political Preference	Model 1
CALURI	0.0130	0.0455***	0.0269***
	(0.015)	(0.016)	(0.008)
Log Income Per Capita	0.545***	0.548***	0.557***
	(0.034)	(0.033)	(0.034)
Avg. Log Income Per Capita	-0.137***	-0.139***	-0.140***
	(0.009)	(0.009)	(0.009)
Endogenize	Reg (1)	Reg (1)	Income (4)
Instrument	Rep.Vote (04)	Rep.Vote (16)	Lag & Demo
N	4,620	4,620	4,620

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. *Housing* indicates whether housing characteristics are controlled in step 1. *Endogenize* indicates whether income or regulation is treated as endogenous. The number of instruments is listed in the parenthesis. The instruments used to endogenize a variable are listed under *Instrument*. *Demo* includes the share of high education, the population age, and the share of high-tech jobs.

Table A16b. Benchmark and Endogenous Regulation: Parameters and Marginal Effects (2012-2017)

Parameter	2004 Political Preference	2016 Political Preference	Model 1
θ	0.0587**	0.0832***	0.0654***
	(0.026)	(0.024)	(0.010)
ϕ	0.442***	0.451***	0.456***
	(0.045)	(0.047)	(0.043)
Marginal Effect	2004 Political Preference	2016 Political Preference	Model 1
CALURI	0.0541**	0.0767***	0.0602***
	(0.024)	(0.023)	(0.009)
Log Income Per Capita	0.558***	0.557***	0.572***
	(0.055)	(0.056)	(0.055)
Avg. Log Income Per Capita	-0.142***	-0.143***	-0.146***
	(0.014)	(0.014)	(0.014)
Endogenize	Reg (1)	Reg (1)	Income (4)
Instrument	Vote (04)	Vote (16)	Lag & Demo
N	1,144	1,144	1,144

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. *Housing* indicates whether housing characteristics are controlled in step 1. *Endogenize* indicates whether income or regulation is treated as endogenous. The number of instruments is listed in the parenthesis. The instruments used to endogenize a variable are listed under *Instrument*. *Demo* includes the share of high education, the population age, and the share of high-tech jobs.

Table A16c. Sargan-Hansen J Test (Endogenous Regulation)

	2004 Political Preference	2004 Political Preference	Model 1
Degree of Freedom	1	1	1
1993-2017 Sample	0.125	0.122	0.209
2012-2017 Sample	0.243	0.240	0.269

Note: the table reports the p-values of the instrument validity tests of Tables A14a and A14b.

A.5.4 Examine the Change of Regulation Over Time: Southern vs Northern California

We examine how the gap of the regulatory impacts in the Southern and Northern California changes over time, and how it is associated with the Southern or Northern regulation relative to the California mean over time.[19] We estimate Model 3 with a South-North division for historical and recent estimates (Table 5d). The upward trend of regulatory impact for California (Figure 8) is associated with an increasing regulatory impact in Southern California (4.3% to 7.2%, closer to the regulatory impact in Northern California which is relatively unchanged: 7.2% to 6.7%). We compare CALURI and TCLURI in the South and North to infer how regulation changes from 2006 to 2018, relative to the California mean. We find the average regulation in the Southern California tightens (-0.043 to 0.104) relative to the average regulation in the Northern California (0.051 to -0.085).

We find suggestive evidence that increasing population density may be associated with the time-varying regulatory impact in Southern California. We report the population density from the 2000 and 2010 Decennial Census by South-North division or/and by the principal city status in Table AZ. The South (5.0%) witnesses faster growth of population density than the North (4.5%), which is largely attributed to the non-principal cities in the South (12.3%). Southern California sees a stronger regulatory impact over time, associated with denser population in the principal cities in the South and faster growth of population density in the non-principal cities.[20]

Table 5d. Estimation by Northern and Southern Division: Parameters and Marginal Effect

Parameter	Model 3	Model 3	Model 3	Model 3
θ	0.0781***	0.0464***	0.0723***	0.0784***
	(0.013)	(0.010)	(0.019)	(0.011)
ϕ	0.604***	0.271***	0.661***	0.164***
	(0.031)	(0.037)	(0.040)	(0.054)
Marginal Effect	Model 3	Model 3	Model 3	Model 3
CALURI	0.0720***	0.0427***	0.0666***	0.0723***
	(0.012)	(0.009)	(0.017)	(0.010)
Log Income Per Capita	0.749***	0.346***	0.823***	0.203***
	(0.037)	(0.047)	(0.043)	(0.068)
Avg. Log Income Per Capita	-0.192***	-0.0878***	-0.210***	-0.0519***
	(0.010)	(0.012)	(0.012)	(0.017)
Endogenize	Income (4)	Income (4)	Income (4)	Income (4)
Instrument	Lag & Demo	Lag & Demo	Lag & Demo	Lag & Demo
Sample	1993-2017	1993-2017	2012-2017	2012-2017
Division	Northern	Southern	Northern	Southern
N	2,085	2,535	532	612

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. A linear model is used to separate housing price variations due to housing, regional and macro controls in step 1, while GMM is used to estimate the model parameters in step 2. The estimation in step 1 is based on housing transactions from 1993 to 2017 in California. The controls used in step 1 include 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 days with good air quality. *Endogenize* indicates whether income or regulation is treated as endogenous.

[19] Southern California includes 10 southernmost counties of 58 counties in California (Imperial, Kern, Los Angeles, Orange, Riverside, San Bernardino, San Diego, Santa Barbara, San Luis Obispo and Ventura).

[20] As is shown in the next section, regulatory impact increases in per capita income. The Northern California sustains high regulatory impact over time by keeping per capita income growing faster than the California average (Figure 4).

The number of instruments is listed in the parenthesis. The instruments used to endogenize a variable are listed under *Instrument*. *Demo* includes the share of high education, the population age, and the share of high-tech jobs.

Table A9. Population and Housing Density: 2000-2010

Census Year	Principal City	Southern CA	Population Density	Housing Density	Growth: Pop. Density	Growth: Housing Density
2000	0	0	2,921	1,062		
2010	0	0	3,118	1,150	0.067	0.083
2000	1	0	4,350	1,626		
2010	1	0	4,596	1,763	0.057	0.085
2000	0	1	2,621	906		
2010	0	1	2,944	1,017	0.123	0.123
2000	1	1	5,040	1,792		
2010	1	1	5,133	1,874	0.018	0.046
Census Year	Principal City	Southern CA	Population Density	Housing Density	Growth: Pop. Density	Growth: Housing Density
2000	0		2,711	953		
2010	0		2,999	1,059	0.106	0.112
2000	1		4,751	1,722		
2010	1		4,907	1,827	0.033	0.061
Census Year	Principal City	Southern CA	Population Density	Housing Density	Growth: Pop. Density	Growth: Housing Density
2000		0	3,692	1,366		
2010		0	3,858	1,457	0.045	0.067
2000		1	3,616	1,270		
2010		1	3,795	1,350	0.050	0.063

Note: Data from 2000 and 2010 Decennial Census. The definition of the principal cities is based on the historical delineation files of the principal cities of metropolitan and micropolitan statistical areas (2006) for year 2000 and the delineation files of the Principal cities (2013) for year 2010. Population or housing density is defined as the total population divided by the total available land (in squared mile).

A.5.5 Heterogeneous Impact of Regulation by Other City Characteristics

In addition to income and regulation, we explore in Table A17 the heterogeneous impact of regulation by other city characteristics, including homeownership rate, share of Hispanic households, political preference measured by the voting share for the Republican party in the presidential election (2004, 2016) and property tax rate.

Homeownership. Cities with lower homeownership rate face a stronger total effect of regulation. The home regulatory and spillover effects are stronger in the cities with high homeownership rate.

Share of Hispanic households. Cities with more Hispanic households face a stronger total effect of regulation. The home regulatory effect across two groups are similar, but the spillover effect in the cities with fewer Hispanic households are stronger.

Political Preference. Cities with smaller Republican support face a stronger total effect, while the home regulatory and spillover effects are stronger in cities with large Republican support. Similar results are found using the political preference in 2016.

Property tax rate. Cities with higher property tax rate face a stronger total effect of regulation, while the home regulatory and spillover effects are stronger in cities with lower property tax rate.

Table A17. Log Housing Price in Los Angeles MSA by City Characteristics

Group by Homeownership Rate		(1) ≤ Median	(2) > Median	(3) ≤ Median	(4) > Median
	CALURI	0.0728***	0.0246***	0.0748***	0.179***

		(0.0019)	(0.0046)	(0.011)	(0.024)
	RRI			0.00206	0.119***
				(0.011)	(0.018)
	Adjusted R^2	0.572	0.709	0.572	0.710
	N	37,926	15,364	37,926	15,364
Share of Hispanic Household		≤ Median	> Median	≤ Median	> Median
	CALURI	0.0295***	0.0639***	0.204***	0.208***
		(0.0025)	(0.0041)	(0.015)	(0.014)
	RRI			0.170***	0.127***
				(0.014)	(0.012)
	Adjusted R^2	0.482	0.785	0.484	0.787
	N	35,399	17,891	35,399	17,891
Voting Share for the Republican party in 2004 Presidential Election		≤ Median	> Median	≤ Median	> Median
	CALURI	0.0403***	0.0316***	0.130***	0.460***
		(0.0018)	(0.0040)	(0.011)	(0.027)
	RRI			0.0923***	0.337***
				(0.011)	(0.021)
	Adjusted R^2	0.553	0.757	0.554	0.761
	N	31,198	22,092	31,198	22,092
Voting Share for the Republican party in 2016 Presidential Election		≤ Median	> Median	≤ Median	> Median
	CALURI	0.0403***	0.0316***	0.130***	0.460***
		(0.0018)	(0.0040)	(0.011)	(0.027)
	RRI			0.0923***	0.337***
				(0.011)	(0.021)
	Adjusted R^2	0.553	0.757	0.554	0.761
	N	31,198	22,092	31,198	22,092
Property Tax Rate		≤ Median	> Median	≤ Median	> Median
	CALURI	0.0269***	0.0794***	0.225***	0.107***
		(0.0039)	(0.0018)	(0.027)	(0.010)
	RRI			0.171***	0.0272***
				(0.022)	(0.010)
	Adjusted R^2	0.662	0.579	0.664	0.579
	N	16,492	36,798	16,492	36,798

Note: robust standard errors in the parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.010$. The dependent variable is the log housing prices. 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, log mile distance to the Pacific coast, the number of days with good air quality. The sample is the property sales in Los Angeles and Orange counties in 2016.

A.5.6 Heterogeneous Impact of Regulation by Housing Characteristic

We examine how regulatory impacts vary by property age, access to employment and housing type. Access to employment is measured by the mile distance from each property to the nearest CBD in a metro area, while housing type is indexed by the number of bedrooms and the number of full bathrooms.

Table A18a divides the sales in the Greater Los Angeles by age into 4 groups (0-10 years, 10-30 years, 30-65 years and more than 60 years) and examines the heterogeneous impacts of regulation on housing prices using OLS. 10 years, 30 years and 65 years are close to the 5th, 25th and 75th percentiles of the property age distribution respectively in the Greater Los Angeles in 2016. We find the total regulatory effects estimated without RRI is decreasing in the property age, going from 12.6% for properties built in 0-10 years to 4.5% for properties built more than 65 years. When the regulatory surrounding is controlled, the home regulatory and the spillover effects of properties built in 0-10 years are 30.7% and 19% respectively. Older properties are much less impacted by regulation. We find the regulatory impacts on properties built 10-30 years ago are close to those built 30-65 years ago (20.6% and 12.4% for the former and 19.9% and 13.7% for the latter). For properties more than 65 years old, we find the marginal effects of CALURI and RRI are not even significant.

Table A18b examines sales within 40 miles in Greater Los Angeles by the distance from a property to the CBD by quartiles (0-5.7 mi, 5.7-9.1 mi, 9.1-13.3 mi, 13.3-40 mi). The mean commuting time is about 30.4 minutes in Los Angeles county, 27.2 minutes in Orange county and 26 minutes in Ventura county and the mean commuting distance in LA MSA is about 9 miles.[21] We find properties that are 9.1 – 13.3 miles from CBDs (or 30 – 45 minutes in commuting time) show the strongest total impact of regulation (12.9%), while properties that are closest to the CBDs (0-5.7 mi) show the weakest total impact (0.6% and insignificant). If the regulatory surrounding is controlled, the group of 9.1-13.3 mi shows the strongest home regulatory impact (30.4%) and second highest spillover effect (17.9% compared to the highest spillover effect 19.9% for the group of 0-5.7 mi).

Table A16c divides sales in the Greater Los Angeles by housing type. We report 11 sets of estimates that vary by the number of bedrooms and full bathrooms and have at least 1,000 observations or 1.6% of the sample. Properties with 3B/2B (3 bedrooms and 2 bathrooms), 2B/2B and 2B/1B are the most common housing types, with the total regulatory effect to be 5.9%, 7.1% and 1.6% respectively. We find the total regulatory effect increases with the number of bathrooms (with the number of bedrooms fixed). We don't find a similar relationship between total regulatory effect and the number of bedrooms (with the number of bathrooms fixed). However, if regulatory surrounding is controlled, we find both the home regulatory and the spillover effects are increasing in the number of bedrooms.

[21] The mean commuting time is calculated by dividing the aggregate travel time to work for all workers by the total number of workers who commute. Data comes from the 2012-2016 wave of ACS 5-year summary file. The mean commuting miles comes from the estimate by Kneebone and Holmes (2015). The upper bound of 40 miles is more than 20% higher than the distance traveled at the California highway speed limit for the length of the mean commuting time (65 mph*0.5 hour) and excludes properties that are located too far to access job opportunities in CBDs.

Table A18a. Log Housing Price in Greater Los Angeles by Property Age

	(1)	(2)	(3)	(4)
	0-10 years	0-10 years	10-30 years	10-30 years
CALURI	0.126***	0.307***	0.0853***	0.206***
	(0.0063)	(0.040)	(0.0036)	(0.017)
RRI		0.190***		0.124***
		(0.040)		(0.017)
Adjusted R^2	0.694	0.699	0.704	0.706
Observations	3,173	3,173	13,047	13,047
	(5)	(6)	(7)	(8)
	30-65 years	30-65 years	65+ years	65+ years
CALURI	0.0602***	0.199***	0.0447***	0.0299*
	(0.0020)	(0.010)	(0.0026)	(0.017)
RRI		0.137***		-0.0152
		(0.0099)		(0.017)
Adjusted R^2	0.544	0.547	0.497	0.497
Observations	29,670	29,670	15,373	15,373

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. The dependent variable is the log housing prices. 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, log mile distance to the Pacific coast, the number of days with good air quality. The sample is the property sales in Los Angeles, Orange and Ventura counties in 2016. Models are estimated using OLS.

Table A18b. Log Housing Price in Greater Los Angeles by Distance to the Core City Quartiles

	(1)	(2)	(3)	(4)
	min-Q1	min-Q1	Q1-Q2	Q1-Q2
CALURI	0.00609	0.206***	0.0183***	0.142***
	(0.0038)	(0.023)	(0.0026)	(0.022)
RRI		0.199***		0.128***
		(0.023)		(0.022)
Adjusted R^2	0.417	0.420	0.499	0.500
Observations	14,489	14,489	14,519	14,519
	(5)	(6)	(7)	(8)
	Q2-Q3	Q2-Q3	Q3-max	Q3-max
CALURI	0.129***	0.304***	0.0206***	0.0967***
	(0.0031)	(0.015)	(0.0033)	(0.021)
RRI		0.179***		0.0671***
		(0.015)		(0.018)
Adjusted R^2	0.634	0.639	0.697	0.697
Observations	14,555	14,555	14,529	14,529

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. The dependent variable is the log housing prices. 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, log mile distance to the Pacific coast, the number of days with good air quality. The sample is the property sales in Los Angeles, Orange and Ventura counties in 2016 that are within 40 miles from the nearest core cities. Models are estimated using OLS. Q0 = 0; Q1 = 5.7 miles; Q2 = 9.1 miles; Q3 = 13.3 miles; max = 40 miles.

Table A18c. Log Housing Price in Greater Los Angeles by Housing Type

	(1) 1 Bed 1 Bath	(2) 1 Bed 1 Bath	(3) 2 Bed 1 Bath	(4) 2 Bed 1 Bath	(5) 3 Bed 1 Bath	(6) 3 Bed 1 Bath
CALURI	0.0613***	0.0719*	0.0160***	0.0805***	0.00118	0.0970***
	(0.0064)	(0.043)	(0.0034)	(0.029)	(0.0054)	(0.030)
RRI		0.0107		0.0655**		0.0964***
		(0.042)		(0.029)		(0.028)
Adjusted R^2	0.318	0.318	0.283	0.284	0.233	0.234
Observations	2,789	2,789	6,866	6,866	4,308	4,308
	(7) 2 Bed 2 Bath	(8) 2 Bed 2 Bath	(9) 3 Bed 2 Bath	(10) 3 Bed 2 Bath	(11) 4 Bed 2 Bath	(12) 4 Bed 2 Bath
CALURI	0.0713***	0.148***	0.0593***	0.191***	0.0213***	0.238***
	(0.0034)	(0.018)	(0.0031)	(0.014)	(0.0060)	(0.032)
RRI		0.0785***		0.131***		0.214***
		(0.018)		(0.013)		(0.031)
Adjusted R^2	0.458	0.459	0.498	0.501	0.454	0.461
Observations	8,446	8,446	14,835	14,835	6,187	6,187
	(13) 2 Bed 3 Bath	(14) 2 Bed 3 Bath	(15) 3 Bed 3 Bath	(16) 3 Bed 3 Bath	(17) 4 Bed 3 Bath	(18) 4 Bed 3 Bath
CALURI	0.0750***	0.0883***	0.0898***	0.158***	0.0938***	0.254***
	(0.0076)	(0.034)	(0.0047)	(0.021)	(0.0063)	(0.026)
RRI		0.0136		0.0689***		0.163***
		(0.034)		(0.021)		(0.025)
Adjusted R^2	0.590	0.590	0.607	0.608	0.615	0.619
Observations	1,901	1,901	4,911	4,911	4,668	4,668
	(19) 5 Bed 3 Bath	(20) 5 Bed 3 Bath	(21) 4 Bed 4 Bath	(22) 4 Bed 4 Bath		
CALURI	0.0812***	0.332***	0.197***	0.315***		
	(0.018)	(0.059)	(0.014)	(0.051)		
RRI		0.260***		0.124**		
		(0.055)		(0.051)		
Adjusted R^2	0.435	0.444	0.448	0.451		
Observations	1,088	1,088	1,044	1,044		

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. The dependent variable is the log housing prices. 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, log mile distance to the Pacific coast, the number of good days (air quality). The sample is the property sales in Los Angeles, Orange and Ventura counties in 2016. Models are estimated using OLS.

A.6 Comparison of the Estimation Results Based on Terner and Wharton Surveys

A.6.1 Terner Center California Land Use Survey

Mawhorter and Reid (2018) conduct a recent survey on California local jurisdictions in 2017-2018, receiving 252 city responses with a response rate of 52%. The response rate is higher than that of the Wharton survey in California (38%). The survey covers a wide range of topics including local zoning, development approval processes, affordable housing policies, and rental regulations. To show the robustness of our previous results, we select topics and questions in the Terner survey that Mawhorter and Reid (2018) identify to be comparable or similar to those in the Wharton survey in addition to the topics that we think are relevant. We use a similar method as CALURI to extract the principal factor of the sub-indices as an aggregate measure of regulation, called TCLURI.

A.6.2 Construction of Sub-indices

We describe how to construct from the Terner survey the following 8 sub-indices that are comparable to those underlying CALURI.

Development Constraint Index. There are 15 questions related to the constraints on the development with question tag *cns_*. Each question asks about the degree to which an aspect constrains development, going from the lowest degree 1 (not a constraint) to the highest degree 6 (a severe constraint). We calculate the sum of the constraint degrees from those questions and define it as the Development Constraint Index. The larger the development constraint index, the more types of constraints imposed on housing development.

Project Approval Index. There are 6 questions about the degree to which single-family or multi-family housing projects are approved, permitted or completed, with the lowest degree 1 (never/hard) to the highest (always/easy) and the question tag *apr_*. We calculate the mean of the ordinal answers about approval, permission and completion for single-family housing and similarly for the multi-family housing. We then, and define the Project Approval Index as the difference between 7 and the average across the last-step summation across housing types. The index thus ranges from 1 to 6. The higher the project approval index, the harder a housing project is to be approved, permitted or completed.

Approval Time Index. We examine 8 questions about expected approval time of single-family or multi-family housing projects with the question tag *apt_*. There are 4 levels, with level 1 for less than 2 months to level 4 for more than a year. We sum those 8 ordinal variables and define it as the Approval Time Index. The larger the index is, the longer a housing project needs for approval.

Zoning Restriction Index. We examine the survey questions with the tag *zon_* and with sufficient city response. We define a city with the maximum density below the median of the sample as regulated by the maximum density. Similarly, we categorize cities by the height limit. On the other hand, we define a city with the minimum lot size above the median of the sample as regulated by the minimum lot size. Similarly, we categorize cities by the minimum lot width. Those zoning restrictions are separately surveyed for single-family and multi-family housing. The large the zoning restriction index as the sum of the 8 indicators, the more types restrictions are.

Affordable Restriction Index. There are 7 questions related to the affordable housing with the question tag *aff_*. Each question asks about whether there is reduced requirement, lower cost or more incentive to building affordable housing. We assign a value of 8 for jurisdictions without any benefit of affordable housing supply, and decrease the index by 1 for every question with a positive answer. The larger the affordable restriction index, the smaller benefit offered to build affordable housing.

Approval Delay Index. We combine the answers from 9 questions asking about the reasons of delay application approvals with the question tag *fac_*. We count the total number of reasons in the application delay and define it as the Approval Delay Index. The larger the index, the more likely an application is delayed.

Construction Limit Index. There is 1 question asking about whether there is a limit on the housing built in a year, with the question tag *lmt_*. We thus define a binary construction limit index that takes value 1 if the answer to the question is a yes, and takes value 0 if otherwise.

Local Opposition Index. There are 2 questions about how often local citizens or officials actively oppose local residential development, with the question tag *opp_*. The answers ranging from the lowest degree 1 (never) to the highest degree 6 (always). We define the Local Opposition Index as the sum of the answers to those questions. The larger the index is, the more development burden in a jurisdiction.

A.6.3 Terner Center Land Use Regulation Index (TCLURI)

We define the principal factor of 8 sub-indices defined above as TCLURI. The factor loadings in descending order are: Development Constraint Index (0.43), Local Opposition Index (0.34), Approval Time Index (0.19), Approval Delay Index (0.08), Project Approval Index (0.06), Construction Limit Index (0.01), Affordable Restriction Index (-0.02), Zoning Restriction Index (-0.02).

Because the single index is a predicted score of the regression with the standardized value of those sub-indices and a zero constant, we re-normalize the predicted score to zero mean and unit variance, similar to what we do for CALURI. There are 102 cities that are covered by both the Wharton and the Terner survey. The population weighted correlation of CALURI and TCLURI across those cities is 0.43. In Figure A11, we plot CALURI against TCLURI for cities covered by both surveys.

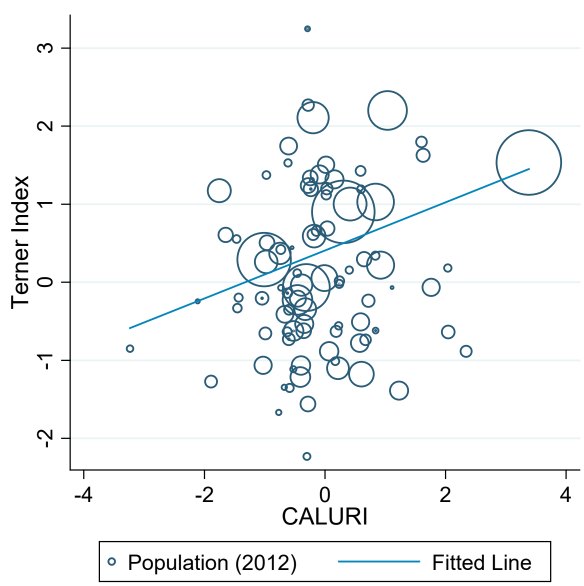


Figure A11: Scatter plot of CALURI (Wharton survey) and TCLURI (Terner survey).

A.6.4 Comparison of the Estimation Results Based on Terner and Wharton Surveys

Besides the Terner-Wharton comparison for California, in Table A19, we compare the reduced-form estimation results for Greater Los Angeles based on the Terner survey and the Wharton survey. We report the specifications without and with relative restrictiveness index (Models with odd numbers exclude RRI, while Models with even numbers include RRI). Results from both surveys show that excluding RRI will underestimate the home regulatory effect. Models 1-4 compare the marginal effects of regulation using the subset of overlapping cities covered by the Terner survey (Models 1-2) and the Wharton survey (Models 3-4). There are 27 cities that responded to both surveys. The total regulatory effect estimated by Models 1 and 3 show no statistical difference. We find the home regulatory and the spillover effects based on the Terner survey (Model 2) are smaller than the Wharton survey. In Models 5-8, we instead examine all property sales from all available cities in Greater Los Angeles, 72 cities in the Terner survey (Models 5-6) and 55 cities in the Wharton survey (Models 7-8). The total regulatory effect is 2.5% from the Terner survey (Model 5), smaller than 6.7% from the Wharton survey (Model 7). The home regulatory and spillover effects are smaller in the Terner survey (Model 6) than in the Wharton survey (Model 8).

Table A19. Comparison of the Estimated Results for Greater Los Angeles: Terner vs Wharton Surveys

	Model 1 Terner	Model 2 Terner	Model 3 Wharton	Model 4 Wharton	Model 5 Terner	Model 6 Terner	Model 7 Wharton	Model 8 Wharton
Regulation	0.0681***	0.189***	0.0660***	0.134***	0.0252***	0.0887***	0.0670***	0.162***
	(0.0030)	(0.0064)	(0.0015)	(0.0089)	(0.0019)	(0.0052)	(0.0014)	(0.0074)
RRI		0.152***		0.0703***		0.0684***		0.0964***
		(0.0069)		(0.0089)		(0.0048)		(0.0073)
Cities	Overlapping Cities	Overlapping Cities	Overlapping Cities	Overlapping Cities	Terner Cities	Terner Cities	Wharton Cities	Wharton Cities
No.of Cities	27	27	27	27	72	72	55	55
N	46,129	46,129	46,129	46,129	75,838	75,838	61,263	61,263

Note: robust standard errors in the parentheses. * p<0.10, ** p<0.05, *** p<0.010. Each observation is indexed by county, city and year. Regulation indices are CALURI in the Wharton specifications and TCLURI in the Terner specifications. The dependent variables are the log sales prices in 2016 in Greater Los Angeles (Los Angeles, Orange, Ventura Counties). 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, log mile distance to the Pacific coast, the number of days with good air quality.

A.7 Model and Estimation with Amenity Effect

In the main text, we consider a model where there is no direct effect of regulation on the housing demand side. We relax the assumption in the section by including regulation as a factor in the function of the demand shifter in addition to the income. This will generate the amenity effect as another direct effect of regulation. The following assumption on the demand shifter captures the effect in a reduced-form.

$$A_j = Z_j^{\phi-1} \tau_j^{\eta} \tag{12}$$

with the moving probability to city j will be updated to

$$q_j(p) = \frac{Z_j^{\phi} \tau_j^{\eta} p_j^{-\alpha}}{\sum_{k \in S} Z_k^{\phi} \tau_k^{\eta} p_k^{-\alpha}} \tag{13}$$

The derivation of the housing price equation can be still applied to the extended case. The extended log price equation can be expressed as follows.

$$\begin{aligned}
\ln p_{ijmt} &= \beta_0 + f_1 + f_2 + f_3 + f_4 + \varepsilon_{ijmt} \\
\text{where } f_1 &= [\theta(1-\tfrac{1}{2}\lambda) - \eta(1-\theta)(\lambda-\tfrac{1}{2})]\cdot CALURI_j \\
&\quad +(\tfrac{3}{2}-\lambda)(1-\theta)\phi z_{mt} + (\lambda-\tfrac{1}{2})(1-\theta)\phi z_{0t} \\
f_2 &= X_{ijmt}\gamma,\ f_3 = N_{jmt}\chi,\ f_4 = M_t\nu
\end{aligned} \tag{14}$$

Besides the parametric assumptions we made before, we add one more condition to identify the additional parameter. We use a relationship between η and ϕ, using the correlation of regulation and the log per capita city income. We log-linearize the identity of the demand shifter and transform it into the following auxiliary regression.

$$z_j = cons + \tfrac{\eta}{1-\phi}\ln\tau_j + controls_{jm} + e_{jm} \tag{15}$$

where *cons* is a constant, *controls* includes demographic variables the demand shifter is the residuals. The city-level per capita income is aggregated from the census tract per capita income using tract population as the weight and comes from the summary file of 2012-2016 ACS 5-year. We add demographic variables at the MSA level from Moody's Analytics and ACS as controls, including the share of high-tech jobs, the population age, the share of high education (high school, in college, graduate), race and ethnicity share (white, black), net migration, the employment, total population and Republican support.[22] We find the estimated coefficient of $\ln(\tau_j)$ to be 0.04, which is insignificant and economically small. We re-estimate Model 4 in Table 5 and find that the parameters and the marginal effects are not quantitatively different. Due to the low correlation between per capita income and CALURI, leaving out the amenity effect doesn't substantially affect our estimation in the main paper.

[22] The share of high-tech jobs from the regional dataset of Moody's Analytics collected from BLS and BEA, the mean household age from American Community Survey (ACS) Public Use microdata, and the share of high school/college/graduate from ACS microdata. Data on the net migrants (in thousand) and total population (in thousand) come from the regional data set of Moody's Analytics collected from the Census Bureau. Data on employment (in thousand) comes from Moody's Analytics collected from BLS (CES and QCEW). The black and white shares come from ACS microdata.

Table A20a. Estimation: Auxiliary Regression

	Model 1		Model 2		Model 3	
CALURI	-0.00351	(0.037)	0.0294	(0.028)	0.0406	(0.027)
log(Age)	0.0203	(0.034)	-0.0772***	(0.029)	-0.0717**	(0.028)
log(BlackShare)			2.118	(2.081)	2.004	(1.966)
log(White Share)			0.0870	(0.112)	0.110	(0.106)
log(Graduate Share)			-0.132	(0.457)	-0.196	(0.431)
log(In College Share)			0.0380	(0.250)	0.143	(0.238)
log(High School Share)			-0.630	(1.365)	-1.548	(1.304)
Net Migration			-1.266	(1.564)	-2.673*	(1.509)
log(Employment)			0.00284	(0.013)	-0.00509	(0.012)
log(Tech Job Share)			0.0256	(0.054)	0.0101	(0.051)
log(Population)			0.158	(0.121)	0.124	(0.114)
LOR(Rep.Support)					0.195***	(0.043)
Constant	9.944***	(0.375)	1.890	(9.284)	1.034	(8.770)
N	177		177		177	

Table A20b. Estimation: Marginal Effect

	Model 3	
CALURI	0.0331***	(0.008)
Log Income Per Capita	0.511***	(0.033)
Avg.Log Income Per Capita	-0.129***	(0.008)
N	4,620	

Table A20c. Estimation: Parameters

	Model 3	
θ	0.0273***	(0.009)
ϕ	0.393***	(0.026)
η	0.0242***	(0.001)
N	4,620	

A.8 Political Economy of Regulation and Spillover Effect

We discuss the political economy of regulation and how spillover effect measures the distance between optimal regulation in the centralized and decentralized economies. In a non-cooperative economy, growth control policies are set independently by local policy makers. If one city tightens regulation, the general equilibrium effect will push up the housing prices in the neighboring localities in the absence of regulatory change or higher housing demand. Such "demand shock" creates negative externality by increasing housing prices and lowering household welfare in the neighboring localities. The stronger the spillover effect is, the more inter-connected the housing markets are and the more negative externality independent policy making will create.

We make this point more clearly by continuing the two-city example in Figure 1 and characterize the decision problem of local policy makers who decide land use regulation in the presence of regulatory spillovers. We assume two cities are identical except that the political goal of regulation τ_{0j} in city j may differ. The political goal may balance the preference of old households who prefer higher housing prices to protect their equity as well as the preference of young household who prefer low prices for affordable housing. A policy maker in city j cares about both the political goal and household welfare. She sets the local growth control policy τ_j to maximize the following objective function, given the optimal choices of policy makers in the neighboring city $-j$.

$$\max_{\tau_j} \underbrace{-\mu\frac{1}{2}(\ln\tau_j - \ln\tau_{0j})^2}_{political\ goal} \underbrace{-(1-\mu)[\gamma_1\ln\tau_j + \gamma_2(\ln\tau_{-j} - \ln\tau_j) + \gamma_0]}_{household\ welfare}$$

where μ is the weight on the political goal. The first term is a quadratic loss if the optimal regulation deviates from the political goal. The second term measure household welfare and is the indirect household utility evaluated at the equilibrium housing price. The parameters γ_1 and γ_2 control the size of the home regulatory and spillover effects, while the parameter $\gamma_0 > 0$ is a constant that is independent of regulation and yields a positive log price level in the bracket. We assume $\gamma_1 > \gamma_2$ so that the total effect of regulation is positive on housing prices, consistent with what we find in our estimation. We consider the symmetric equilibrium in which policy makers make identical choices.

$$\ln \tau^{NC} = \ln \tau_0 - \frac{1-\mu}{\mu}(\gamma_1 - \gamma_2) > \ln \tau_0 - \frac{1-\mu}{\mu}\gamma_1 = \ln \tau^{CO}$$

If growth control policies are set independently, we settle in the non-cooperative equilibrium regulation τ^{NC} which is an increasing function of the spillover effect γ_2 and a decreasing function of the home regulatory effect γ_1. If the growth control policies are set collectively and we assign equal welfare weight to both cities, we settle in the cooperative equilibrium regulation τ^{CO} which internalizes the externality of the regulatory spillover and depends on the home regulatory effect only. The gap between τ^{NC} and τ^{CO} is determined by the size of the spillover effect γ_2.

Hence, it is important to separate the home regulatory effect from the spillover effect to find the optimal level of regulation. For areas with strong regulatory spillover, collective growth control policy making mitigates negative externality and achieves higher welfare improvement.

A.9 CALURI by MSA and City

Table A21. 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 A21. 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 A21. 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.