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Housing productivity and the social cost of land-use restrictions

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ABSTRACT

We use metro-level variation in land and structural input prices to test and estimate a housing cost function with differences in local housing productivity. Both OLS and IV estimates imply that stringent regulatory and geographic restrictions substantially increase housing prices relative to land and construction input costs. The typical cost share of land is one-third, and substitution between inputs is inelastic. A disaggregated analysis of regulations finds state-level restrictions are costlier than local ones and provides a Regulatory Cost Index (RCI). Housing productivity falls with city population. Typical land-use restrictions impose costs that appear to exceed quality-of-life benefits, reducing welfare on net.

1. Introduction

Many researchers (e.g., Glaeser et al., 2005a; Saiz, 2010) blame land-use restrictions for declining housing affordability. Summers (2014) comments that one of "the two most important steps that public policy can take with respect to wealth inequality" is "an easing of land-use restrictions." Yet such restrictions are also argued to increase local housing demand by improving local quality of life and the provision of public goods (Hamilton, 1975; Brueckner, 1981; Fischel, 1987). Consequently, land-use restrictions could raise house prices either by increasing housing demand or reducing housing supply. That ambiguity makes the restrictions' effects on social welfare difficult to assess.

We resolve this ambiguity using a two-step process. First, we estimate a cost function for housing across metro areas using the prices of land and construction inputs, along with measures of regulatory and geographic restrictions. We call the gap between an area's actual housing prices and the prices predicted by input costs an area's "housing productivity," in the spirit of a Solow (1957) residual. Our results indicate that regulatory land-use restrictions (Gyourko et al., 2008) and geographical constraints (Saiz, 2010) raise the cost of housing relative to input prices, meaning that they lower housing productivity.

Second, we estimate whether land-use restrictions predict high housing prices relative to local wages. Such an effect on residents' "willingness-to-pay" to live in an area would suggest that land-use restrictions improve their quality of life (Roback, 1982). We find, however, that after accounting for the tendency of areas with more desirable natural amenities to be more regulated, willingness-to-pay is no higher in regulated areas than in unregulated ones.

Together, our results imply that the typical land-use restriction reduces social welfare. Observed land-use restrictions raise housing costs by 15 percentage points on average, reducing average welfare by 2.3% of income on net.[1]

Our cost function estimates are particularly novel in that they employ variation in land and construction price across cities. Conditioning on local land prices isolates the supply-side effects of land-use restrictions on housing prices from their demand-side effects. Our main results hold whether we estimate parameters using ordinary least squares (OLS) or instrumental variable (IV) methods. The estimates imply that land typically accounts for one-third of housing costs and that the elasticity of substitution between inputs is below one. Our results regarding land-

[1] We calculate those magnitudes by comparing the increase in housing costs implied by moving from the fifth percentile of costs imposed by land-use regulation to the average level (15%), and scaling the implied increase in costs by housing's share of the average expenditure bundle of 16%.

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use restrictions also hold when we impose plausible alternative values for these parameters.[2]

Our new measure of metropolitan housing productivity supplements other metropolitan indices of economic value, namely productivity indices for firms in the traded sector—as in Beeson and Eberts (1989), Gabriel and Rosenthal (2004), Shapiro (2006), and Albouy (2016)—and indices of quality of life—as in Roback (1982), Gyourko and Tracy (1991), Albouy (2008), and others. Estimated housing productivity levels vary widely, with a standard deviation equal to 23% of total housing costs. While some assume (e.g., Rappaport, 2008) that productivity levels in traded and housing sectors are equal, we find the two are negatively correlated across metro areas.

We consolidate the predicted efficiency loss of observed land-use regulations into a "Regulatory Cost Index," or RCI. The RCI measures the extent to which observed regulations reduce housing productivity. It has a cardinal economic interpretation given by the efficiency costs imposed by a variety of regulations. The RCI explains two-fifths of the variance between input costs and output prices. It also rises along with city population and density. This last result suggests that endogenous local politics may impose a diseconomy of urban scale.

There are important antecedents to our work on housing productivity. Rose (1992) finds that geographic restrictions in Japan raise land and housing values in 27 cities. Ihlanfeldt (2007) documents that land-use regulations predict higher housing prices but lower land values using assessment data from 25 Florida counties. Glaeser and Gyourko (2003, 2005) document that housing and land values differ most in cities where rezoning requests take the longest using data from 20 U.S. cities. They also argue that regulations push the unit prices in tall Manhattan buildings above their marginal construction costs. These extra costs do not offset the estimated benefits of preserved views. Our study builds upon these approaches by providing a unified framework for measuring the net welfare effects of land-use regulation across a wide range of U.S. metro areas. Waights (2015) builds on our approach using panel data and finds similar results for England, including low factor substitution and negative welfare consequences of land-use restrictions.

2. A model of housing costs and price determination

Our econometric model embeds a cost function for housing within a general-equilibrium model of urban areas, similar to Roback (1982) and Albouy (2016). The national economy contains many cities indexed by j, which produce a numeraire good, X, which is traded across cities, and housing, Y, which is not traded across cities, and has a local price p_j.[3]

2.1. Housing costs, productivity, and supply

Firms produce housing, Y, with land, L, and structural inputs, M. While we refer to the latter loosely as "construction" inputs, they include time and capital costs of maintenance, renovation, and building. The production function for housing obeys the relationship:

$$Y_j = A_j^Y F(L, M; B_j^Y) \tag{1}$$

where F is concave and exhibits constant returns to scale at the firm level.[4] Housing productivity, A_j^Y, is a city-specific characteristic that may vary with characteristics such as population or regulatory environment. B_j^Y captures factor bias in city j, or the relative productivity of land to construction inputs.[5]

We assume that input and output markets are perfectly competitive.[6] Land earns a city-specific price, r_j, while construction inputs cost v_j per unit. Marginal and average costs are given by the unit cost function $c(r_j, v_j; B_j^Y)/A_j^Y \equiv \min_{L,M}\{r_j L + v_j M : A_j^Y F(L, M; B_j^Y) = 1\}$. The equilibrium condition for housing output is that in every city j that has positive production, housing prices should equal unit costs:[7]

$$p_j = c(r_j, v_j; B_j^Y)/A_j^Y. \tag{2}$$

A first-order log-linear approximation of Eq. (2) expresses how housing prices vary with input prices and productivity: $\hat{p}_j = \phi\hat{r}_j + (1-\phi)\hat{v}_j - \hat{A}_j^Y$, where $\hat{z}_j$ represents, for any variable z, city j's log deviation from the national average, $\bar{z}$: $\hat{z}_j = \ln z_j - \ln \bar{z}$. ϕ is the cost share of land for the typical city. Thus, $\hat{p}_j$, $\hat{r}_j$, and $\hat{v}_j$ represent housing-price, land-value, construction-price differentials, or "indices," for each city j. A_j^Y is normalized so that a one-point increase in $\hat{A}_j^Y$ corresponds to a one-point reduction in log costs.

A second-order approximation of Eq. (2) reveals two more parameters, the elasticity of substitution, σ, and differences in factor bias, B_j^Y:

$$\hat{p}_j = \phi\hat{r}_j + (1-\phi)\hat{v}_j + \frac{1}{2}\phi(1-\phi)(1-\sigma)(\hat{r}_j - \hat{v}_j - \hat{B}_j^Y)^2 - \hat{A}_j^Y, \tag{3}$$

The data will indicate that $\sigma < 1$ if output prices increase in the square of the factor-price differences, $(\hat{r}_j - \hat{v}_j)^2$. Factor biases against land, $-\hat{B}_j^Y$, have a similar effect. When $\sigma \neq 0$, the cost-share of land in a particular city j, ϕ_j, can deviate from the typical share, ϕ. This deviation depends on input prices and factor bias according to the approximation:

$$\phi_j = \phi + \phi(1-\phi)(1-\sigma)(\hat{r}_j - \hat{v}_j - \hat{B}_j^Y). \tag{4}$$

When $\sigma < 1$, the local land share rises with the price of land relative to construction inputs, $\hat{r}_j - \hat{v}_j$, and falls with land's factor bias, $\hat{B}_j^Y$.

Local housing supply differences across cities are approximated by:

$$\begin{aligned}\hat{Y}_j &= \hat{L}_j + \sigma\frac{1-\phi_j}{\phi_j}\left(\hat{p}_j - \hat{v}_j\right) + \left(1 + \sigma\frac{1-\phi_j}{\phi_j}\right)\hat{A}_j^Y + \left(1-\phi_j\right)(1-\sigma)\hat{B}_j^Y \\ &= \hat{L}_j + \eta_j\left(\hat{p}_j - \hat{v}_j\right) + \left(1+\eta_j\right)\hat{A}_j^Y + \left(1 - \phi_j - \phi_j\eta_j\right)\hat{B}_j^Y\end{aligned} \tag{5}$$

where $\eta_j \equiv \sigma\left(1-\phi_j\right)/\phi_j$ is the local partial-equilibrium own-price elasticity of housing supply, which falls in the cost share of land, ϕ_j. More generally, Eq. (5) expresses several channels that may affect housing supply. Those concerning overall land supply, $\hat{L}_j$, are not addressed

[2] An expanded model with factor bias suggests land-use restrictions lower the relative value of productivity of land. When we examine the separate effects of 11 sub-indices provided by the Wharton Residential Land-Use Restriction Index, we find state political and court involvement predict the largest increases in costs.

[3] To simplify, we assume away federal taxes and land in the traded sector.

[4] The production model is meant to apply to all housing, not only to new construction. The use of a single function to model the production of a heterogeneous housing stock was first established by Muth (1969). In the words of Epple et al. (2010, p. 906), "The production function for housing entails a powerful abstraction. Houses are viewed as differing only in the quantity of services they provide, with housing services being homogeneous and divisible. Thus, a grand house and a modest house differ only in the number of homogeneous service units they contain." This abstraction also implies that a highly capital-intensive form of housing, e.g., an apartment building, can substitute in consumption for a highly land-intensive form of housing, e.g., single-story detached houses. Our analysis uses data from owner-occupied properties, accounting for 67% of homes, of which 82% are single-family and detached.

[5] In our primary model we ignore variation in B_j^Y, but we include it in an extended model. Briefly, suppose housing productivity is factor-specific, so that the production function for housing is $Y_j = F(L, M; A_j^Y, B_j^Y) = F(A_j^{YL}L, A_j^{YM}M; 1)$. Then the factor bias B_j^Y in Eq. (1) is captured by the ratio $B_j^Y = A_j^{YL}/A_j^{YM}$. Appendix A shows that $\hat{A}_j^Y = \phi\hat{A}_j^{YL} + (1-\phi)\hat{A}_j^{YM}$ and $\hat{B}_j^Y = \hat{A}^{YL} - \hat{A}^{YM}$.

[6] Many studies support the hypothesis that the construction sector is competitive. Glaeser et al. (2005b) report that "...all the available evidence suggests that the housing production industry is highly competitive." Basu et al. (2006) calculate returns to scale in the construction industry as unity, indicating firms in construction have no market power. On the output side, competition seems sensible as new homes must compete with the stock of existing homes. Nevertheless, if markets are imperfectly competitive, then A_j^Y will vary inversely with the mark-up on price above cost.

[7] In previous drafts, we considered when this condition could be slack. Low-growth markets exhibited slackness in a manner consistent with Glaeser and Gyourko (2005), but this had little effect on other results.

here. Housing productivity increases housing supply by lowering factor costs, raising output by $\eta_j \hat{A}_j^Y$, which then frees up land to supply additional housing by an amount $\hat{A}_j^Y$. If $\sigma < 1$, land-biased productivity also increases supply directly. Furthermore, the price elasticity η_j is higher in places where the local cost share of land, ϕ_j, is lower.[8]

2.2. Simultaneous determination of housing and land prices

This section considers how input and output prices are jointly determined in an equilibrium model of a system of open cities. In addition to housing productivity, A_j^Y, cities j vary in trade productivity, A_j^X, and quality of life, Q_j. Each production sector has its own type of worker, $k = X, Y$, where type-Y workers produce housing. Preferences are represented by $U(x, y; Q_j^k)$, where x and y are personal consumption of the traded good and housing, and Q_j^k varies by worker type. Each worker supplies a single unit of labor and earns wage w_j^k, along with non-labor income, I^k, which does not vary across metros.

Consider the case in which workers are perfectly mobile and preferences are homogeneous. In equilibrium, this requires that workers receive the same utility in all cities, $\bar{u}^k$, for each type. Define s^Y as the expenditure share on housing and t as labor's share of income, assumed equal across sectors. Appendix A shows that this mobility condition implies that the local quality-of-life index is proportional to residents' willingness-to-pay determined by housing prices and wages:

$$\hat{Q}_j^k = s^Y \hat{p}_j - t\hat{w}_j^k,\ k = X, Y, \tag{6}$$

i.e., higher quality of life must offset high prices or low after-tax wages.[9] The aggregate quality of life index is $\hat{Q}_j \equiv \lambda \hat{Q}_j^X + (1-\lambda)\hat{Q}_j^Y$, where λ is the share of labor income in the traded sector. Likewise, the aggregate wage index is $\hat{w}_j \equiv \lambda \hat{w}_j^X + (1-\lambda)\hat{w}_j^Y$.

Traded output has a uniform price of one across all cities. It is produced with Cobb–Douglas technology, with A_j^X being factor neutral. The trade-productivity index is then proportional to the wage index:

$$\hat{A}_j^X = \theta \hat{w}_j^X, \tag{7}$$

where θ is the cost share of labor. Mobile capital, with a uniform price across cities, accounts for remaining costs in the traded sector.

Construction inputs are produced with local labor and traded capital according to the production function $M_j = (N^Y)^a (K^Y)^{1-a}$, implying that $\hat{v}_j = a\hat{w}_j^Y$. This permits us to write an alternative housing productivity measure that uses wages, weighted by the labor's cost share in housing, $a(1-\phi)$:

$$\hat{A}_j^Y = \phi \hat{r}_j + a(1-\phi)\hat{w}_j^Y - \hat{p}_j. \tag{8}$$

The total-productivity index of a city is $\hat{A}_j^{TOT} \equiv s^Y \hat{A}_j^Y + s^X \hat{A}_j^X$,

Combining Eqs. (6), (7), and (8) gives the following system of equations:

$$t\hat{w}_j^X = \lambda^{-1} s^X \hat{A}_j^X \tag{9a}$$

$$s^Y \hat{p}_j = \hat{Q}_j^X + \lambda^{-1} s^X \hat{A}_j^X \tag{9b}$$

$$t\hat{w}_j^Y = \hat{Q}_j^X - \hat{Q}_j^Y + \lambda^{-1} s^X \hat{A}_j^X \tag{9c}$$

$$s^Y \phi \hat{r}_j = \lambda \hat{Q}_j^X + (1-\lambda)\hat{Q}_j^Y + s^X \hat{A}_j^X + s^Y \hat{A}_j^Y = \hat{Q}_j + \hat{A}_j^{TOT} \tag{9d}$$

where $s^Y\phi$ is land's share of income. Housing prices are determined by the traded sector's productivity and the amenities valued by its workers. Wages in the housing sector keep up with those in the traded sector, but are lower insofar as workers in the housing sector prefer the local amenities. Land values capitalize the full value of all amenities; unlike housing prices, these values include housing productivity and quality of life for housing workers. As noted by Aura and Davidoff (2008), improvements in local housing productivity need not reduce the unconditional price of housing. In this model, they raise land values instead.[10]

3. Empirical approach

Here, we adapt a translog functional form for the housing cost function and propose specification tests for it. We also discuss identification from the perspective of our theoretical model and compare our parametric estimation approach to non-parametric approaches that treat housing quantities as a latent variable.

3.1. Adapting and testing the translog cost function

Assume city j's housing productivity and factor bias are determined in part by a vector of observable restrictions, Z_j, which is partitioned into regulatory and geographic components: $Z_j = [Z_j^R, Z_j^G]$. Productivity and bias are also determined by unobserved city-specific components, $\xi_j = [\xi_{Aj}, \xi_{Bj}]$, such that:

$$\hat{A}_j^Y = -Z_j \delta_A - \xi_{Aj} \tag{10a}$$

$$\hat{B}_j^Y = -Z_j \delta_B - \xi_{Bj}. \tag{10b}$$

A positive δ_A indicates that a restriction *reduces* productivity; a positive δ_B indicates that a restriction is biased *against* land. Substituting Eqs. (10a) and (10b) into (3) gives the following reduced-form equation:

$$\hat{p}_j - \hat{v}_j = \beta_1(\hat{r}_j - \hat{v}_j) + \beta_3(\hat{r}_j - \hat{v}_j)^2 + \gamma_1 Z_j + \gamma_2 Z_j(\hat{r}_j - \hat{v}_j) + \zeta_j + \varepsilon_j. \tag{11}$$

The error in this regression comprises two components. The first, ζ_j, is driven mainly by unobservable determinants of productivity and bias:

$$\zeta_j = \xi_{Aj} + \xi_{Bj}\phi(1-\phi)(1-\sigma)\left[Z_j\delta_B + \hat{r}_j - \hat{v}_j + \xi_{Bj}/2 + (Z_j\delta_B)^2/2\right]. \tag{12}$$

The second component, ε_j, may capture sampling, specification, and measurement error.[11] Appendix A provides more detail.

Relaxing the homogeneity assumption gives a more general form of Eq. (11):

$$\begin{aligned}\hat{p}_j = {} & \beta_1\hat{r}_j + \beta_2\hat{v}_j + \beta_3(\hat{r}_j)^2 + \beta_4(\hat{v}_j)^2 + \beta_5(\hat{r}_j\hat{v}_j) + \gamma_1 Z_j \\ & + \gamma_2 Z_j\hat{r}_j + \gamma_3 Z_j\hat{v}_j + \varepsilon_j'.\end{aligned} \tag{13}$$

The first five terms correspond to the general translog cost function (Christensen et al., 1973) with land and construction prices. The last three terms augment it with Z_j and its interactions. The translog is equivalent to the second-order approximation of the cost function (see, e.g., Binswanger, 1974; Fuss and McFadden, 1978) under the homogeneity constraints:

$$\beta_1 = 1 - \beta_2 \tag{14a}$$

$$\beta_3 = \beta_4 = -\beta_5/2 \tag{14b}$$

[8] This is a local approximation. When $\sigma = 1$, differences in price elasticities η_j cannot depend on prices or factor bias, which affect ϕ_j endogenously through (4). Thy must instead be related to exogenous differences in ϕ_j or in land supply elasticities, through $\hat{L}_j$.

[9] Q_j^k is normalized such that $\hat{Q}_j^k$ of 0.01 is equivalent in utility to a 1% rise in total consumption.

[10] Two amendments to the model can create a negative relationship between housing productivity and housing prices. The first is to introduce land into the non-traded sector (Roback, 1982). The second is to introduce heterogeneity in location preference, which is similar to introducing moving costs. The mathematics in these two richer cases are complicated, but are described and simulated in Albouy and Farahani (2017) when $\hat{Q}_j^X = \hat{Q}_j^Y$. As heterogeneity in preferences increase, the city becomes closed, and estimation issues related to simultaneity diminish. At the same time, it becomes more difficult to examine the quality-of-life benefits of land-use restrictions.

[11] This could result from market power or disequilibrium forces causing prices to deviate from costs. See footnotes 6 and 7.

The extended model, with $\delta_B \neq 0$, also imposes the restriction that $\gamma_2 = -\gamma_3$.[12] The econometric model allows us to test for Cobb-Douglas technology, which imposes the restriction $\sigma = 1$ in (3) or, in Eq. (13):

$$\beta_3 = \beta_4 = \beta_5 = 0. \tag{15}$$

The reduced-form coefficients of Eq. (11) correspond to the following structural parameters:

$$\beta_1 = \phi \tag{16a}$$

$$\beta_3 = (1/2)\phi(1-\phi)(1-\sigma) \tag{16b}$$

$$\gamma_1 = \delta_A \tag{16c}$$

$$\gamma_2 = \phi(1-\phi)(1-\sigma)\delta_B = 2\beta_3\delta_B. \tag{16d}$$

Inverting the equations to solve for the structural parameters shows that β_1 identifies the distribution parameter, ϕ, and together with β_3 it identifies the substitution parameter σ. γ_1 identifies how much measures in Z *raise* costs (or conversely, *lower* productivity). γ_2 and β_3 identify how measures in Z bias productivity *against* land when $\gamma_2\beta_3 > 0$.

3.2. Identification, simultaneity, and instrumental variables

The econometric specification in Eq. (13) regresses housing costs $\hat{p}_j$ on land values $\hat{r}_j$, construction prices $\hat{v}_j$, restrictions, $\hat{Z}_j$, and their interactions. With no factor bias ($\hat{B}_j^Y = 0$), the residual represents either unobserved housing productivity, ζ_j, or the more general error term, ϵ_j. This specification isolates supply factors in A_j^Y, which pull the price of housing away from land, from the demand factors in Q_j and A_j^X, which move housing and land prices in the same direction. OLS estimates of the housing-cost parameters will be consistent if $\zeta_j = 0$ and ϵ_j is orthogonal to the regressors.

A simultaneity problem arises if there are unobserved cost determinants $\zeta_j \neq 0$ not absorbed by the controls, Z_j; see Appendix B for technical details. In an open city, high housing productivity raises land values without changing housing prices, as seen in (9b) and (9d). This variation attenuates the estimate of land's share, $\hat{\phi}$, towards zero. Correlation between ζ_j and other cost-function elements may also introduce omitted variable bias.

One solution to these potential problems is to find instrumental variables (IVs) for land values and structural input prices. The model implies that variables that predict quality of life Q_j or trade productivity A_j^X will be relevant in that they will raise land values. To satisfy the exclusion restriction, these variables must be uncorrelated with ζ_j.

3.3. Comparison to alternative estimation techniques

A long literature estimates housing production and cost functions: see, for instance, McDonald (1981) and Thorsnes (1997). Here, we compare our methodology to the related and influential approaches of Epple et al. (2010) and Combes et al. (2017). Those studies estimate the housing production function using developers' optimality conditions for combining land and structure, treating housing quantities as latent variables.

An important advantage of this other approach is that it relies on a direct measure of housing value (price times quantity) per acre. In contrast — as noted by Combes et al. (2017) — our approach requires estimating a cross-sectional housing-price index, which we impute imperfectly using hedonic methods. Additionally, both Epple et al. (2010) and Combes et al. (2017) estimate the housing production function non-parametrically, rather than with a translog form.[13]

[12] While the model assumes constant returns to scale at the firm level, it does not rule out non-constant returns at the city level. Urban (agglomeration) economies of scale will be reflected in A_j^Y, as addressed in Section 6.2.

[13] Combes et al. (2017) also allows for non-constant-returns-to-scale, in contrast to our approach and that of Epple et al. (2010).

The approach taken here has some advantages. Most importantly, it easily accommodates observable productivity shifters such as regulatory and geographic constraints. If correctly specified, the parametric form efficiently estimates cost shares and elasticities of substitution, which are heavily researched and easy to interpret. By focusing exclusively on prices, the method also avoids problems that arise with measured quantities, such as optimization errors, which can attenuate estimates. Finally, the cost function approach can be embedded in an equilibrium system of cities and used to assess the welfare consequences of land-use regulations. Given the approaches' different sets of strengths, we hope that they will be seen as complements rather than substitutes in future research.

4. Data and metropolitan indicators

The residential land-value index used to estimate the housing cost function is adapted from Albouy et al. (2018), who describe it in detail. It is based on market transactions from the CoStar group and uses a regression framework that controls for some parcel characteristics. It applies a shrinkage technique to correct for measurement error due to sampling variation, which is important given sample sizes in smaller metros. It provides flexible land-value gradients, estimated separately for each city using an empirical Bayes-type technique that "borrows" information from other cities with a similar land area. The residential index used in this paper differs from the index in Albouy et al. (2018) in that it: (i) weights census tracts according to the density of residential housing units, rather than by simple land area; (ii) uses fitted values for residential uses, rather than for all uses; and (iii) encompasses all metropolitan land, not only land that is technically urban.

4.1. Housing price, wages, and construction price indices

Housing-price and wage indices for each metro area, j, and year, t, from 2005 to 2010, are based on 1% samples from the American Community Survey (ACS).[14] As Appendix C describes in more detail, we regress the logarithm of individual housing prices $\ln p_{ijt}$ on a set of controls $\mathbf{X}_{ijt}$, and indicator variables for each year-metro interaction, ψ_{ijt}, in the equation $\ln p_{ijt} = \mathbf{X}'_{ijt}\beta + \psi_{ijt} + e_{ijt}$. The indicator variables ψ_{ijt} provide the metro-level indices (or differentials), denoted $\hat{p}_j$.[15]

Metropolitan wage indices are calculated similarly, controlling for worker skills and characteristics, for two samples: workers in the construction industry only, to estimate $\hat{w}_j^Y$, and workers outside the construction industry, to estimate $\hat{w}_j^X$. Appendix Fig. A shows that the two wage measures are highly correlated, but that wages in the construction sector are more dispersed across metros.

Our main price index for structural inputs, $\hat{v}_j$, comes from the Building Construction Cost data from the RS Means company (Waier et al., 2009). The index covers the costs of installation and materials for several types of structures and is common in the literature, e.g., Davis and Palumbo (2008) and Glaeser et al. (2005a). It is provided at the 3-digit zipcode level. When a metro contains multiple 3-digit zipcodes, we weight each by the share of the metro's housing units in each zipcode. Appendix Fig. B shows that construction wages $\hat{w}_j^X$ and construction prices $\hat{v}_j$ are highly correlated.

Columns 2–5 of Table 1 present the housing-price, land-value, construction-cost, and construction-wage indices for a subset of metro

[14] The time period is restricted to those years because prior to 2005, the ACS is too coarse geographically, and our land transaction data end in 2010. We use MSA definitions for the year 2000.

[15] Alternative methods using price differences such as letting the coefficient β vary across cities produce similar indicators (Albouy et al., 2016a). We aggregate the inter-metropolitan index of housing prices, $\hat{p}_{jt}$, across years for display; it is normalized to have mean zero nationally.

Table 1
Indices for selected metropolitan areas, ranked by housing-price index: 2005–2010.

Name of area	Population (1)	Housing price (2)	Land value (3)	Const. price (4)	Wages (Const. only) (5)	Wharton regulatory (z-score) (6)	Geo unavail. (z-score) (7)
Metropolitan areas:							
San Francisco, CA	1,785,097	1.35	1.74	0.24	0.22	1.72	2.14
Santa Cruz-Watsonville, CA	256,218	1.19	0.69	0.14	0.23	0.82	2.07
San Jose, CA	1,784,642	1.13	1.47	0.19	0.22	−0.05	1.68
Stamford-Norwalk, CT	361,024	1.02	1.07	0.14	0.23	−0.56	0.55
Orange County, CA	3,026,786	0.98	1.32	0.06	0.12	0.08	1.14
Santa Barbara-Santa Maria-Lompoc, CA	407,057	0.97	0.71	0.08	−0.04	0.59	2.76
Los Angeles-Long Beach, CA	9,848,011	0.92	1.31	0.08	0.12	0.88	1.14
New York, NY	9,747,281	0.91	1.99	0.29	0.26	−0.17	0.55
Boston, MA-NH	3,552,421	0.64	0.73	0.18	0.10	1.30	0.24
Washington, DC-MD-VA-WV	5,650,154	0.41	1.07	−0.03	0.19	0.89	−0.73
Riverside-San Bernardino, CA	4,143,113	0.26	0.12	0.06	0.12	0.64	0.43
Chicago, IL	8,710,824	0.19	0.61	0.18	0.07	−0.54	0.53
Philadelphia, PA-NJ	5,332,822	0.07	0.25	0.16	0.05	0.69	−0.91
Phoenix-Mesa, AZ	4,364,094	0.00	0.41	−0.10	0.00	1.00	−0.73
Atlanta, GA	5,315,841	−0.29	−0.05	−0.08	0.04	0.08	−1.21
Detroit, MI*	4,373,040	−0.28	−0.33	0.04	−0.02	−0.25	−0.22
Dallas, TX	4,399,895	−0.43	−0.40	−0.17	0.01	−0.67	−0.96
Houston, TX	5,219,317	−0.50	−0.30	−0.14	0.04	−0.07	-1.00
Rochester, NY*	1,093,434	−0.53	-1.43	0.03	−0.05	−0.55	0.07
Utica-Rome, NY*	293,280	−0.66	-1.95	−0.03	−0.32	-1.42	−0.55
Saginaw-Bay City-Midland, MI*	390,032	−0.59	-2.05	−0.01	−0.14	−0.18	−0.61
Metropolitan population:							
Less than 500,000	31,264,023	−0.23	−0.66	−0.36	−0.09	−0.06	−0.04
500,000 to 1,500,000	55,777,644	−0.19	−0.43	−0.29	−0.06	−0.16	−0.05
1,500,000 to 5,000,000	89,173,333	0.10	0.20	0.15	0.02	0.14	0.01
5,000,000+	49,824,250	0.36	0.87	0.22	0.12	0.01	0.09
Standard deviations (pop. wtd.)		0.52	0.86	0.13	0.17	0.96	1.01
Correlation with land values (pop. wtd.)		0.90	1.00	0.64	0.71	0.48	0.56

Land-value index adapted from Albouy et al. (2018) from CoStar COMPS database for years 2005 to 2010. Wage and housing-price data from 2005 to 2010 American Community Survey 1% t samples. Wage indices based on the average logarithm of hourly wages. Housing-price indices based on the average logarithm of prices of owner-occupied units. Regulation Index is the Wharton Residential Land Use Regulatory Index (WRLURI) from Gyourko et al. (2008) Geographic Unavailability Index is the Land Unavailability Index from Saiz (2010). Construction-price Index from R.S. Means. MSAs with asterisks after their names are in the weighted bottom 10% of our sample in population growth from 1980–2010.

areas. They tend to be positively correlated with each other and with metro population, reported in column 1.[16]

4.2. Regulatory and geographic restrictions

Our index of regulatory restrictions comes from the Wharton Residential Land Use Regulatory Index (WRLURI) described in Gyourko et al. (2008). The index reflects the survey responses of municipal planning officials regarding the regulatory process. The responses form the basis of 11 subindices, coded so that higher scores correspond to greater regulatory stringency.[17] Gyourko et al. (2008) construct a single aggregate Wharton index through factor analysis. Our analysis use both their aggregate index and the subindices. The base data for the Wharton index is for the municipal level; we recalculate the index and its subindices at the metro level by weighting the individual municipal values using sampling weights provided by the authors, multiplied by each municipality's population proportion within its metro. We renormalize all of these as $z-$scores, with a mean of zero and standard deviation one, weighting metros by the number of housing units. The subindices are typically, but not uniformly, positively correlated with one another.

Our index of geographic restrictions is provided by Saiz (2010), who uses satellite imagery to calculate land scarcity in metropolitan areas. The resulting "unavailability" index measures the fraction of undevelopable land within a 50 km radius of the city center, where land is considered undevelopable if it is: (i) covered by water or wetlands, or (ii) has a slope of 15° or steeper. We consider both Saiz's aggregate index and his separate indices based on solid and flat land, each of which we re-normalize as a $z-$score.

4.3. Instrumental variable measures

Guided by the model, we consider two instruments for land values. The first is the inverse of the distance to the nearest saltwater coast, a predictor of $\hat{Q}_j$ and $\hat{A}_j^X$. The second is an adaptation of the U.S. Department of Agriculture's "Natural Amenities Scale" (McGranahan et al., 1999), which ought to correlate with $\hat{Q}_j$.[18]

While it is straightforward to show that these instruments are relevant, it is difficult to test the exclusion restriction. That said, we believe the instruments' excludability is plausible given our methods and

[16] We mark metros in the lowest decile of population growth between 1980 and 2010 with a "*" in case the equilibrium condition (2) does not apply well to these areas.

[17] The subindices comprise the approval delay index (ADI), the local political pressure index (LPPI), the state political involvement index (SPII), the open space index (OSI), the exactions index (EI), the local project approval index (LPAI), the local assembly index (LAI), the density restrictions index (DRI), the supply restriction index (SRI), the state court involvement index (SCII), and the local zoning approval index (LZAI).

[18] The natural amenities index in McGranahan et al. (1999) is the sum of six components: mean January temperature, mean January hours of sunlight, mean July temperature, mean relative July humidity, a measure of land topography, and the percent of land area covered in water. We omit the last two components in constructing the IV because they are similar to the components of the Saiz (2010) index of geographic restrictions to development. The adapted index is the sum of the first four components averaged from the county to metro level.

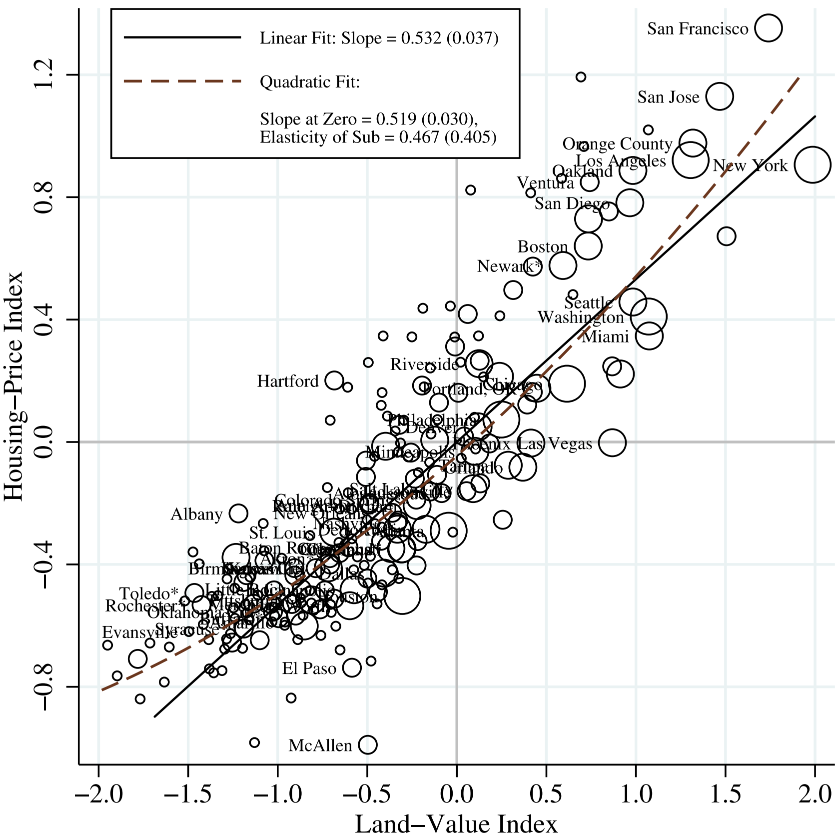


Fig. 1. Houseprices and land values across metropolitan areas, 2006–10.

controls. *A priori*, the inverse distance to the coast should be uncorrelated with housing productivity conditional on geographical constraints to development. At first, the documented correlation between weather and construction activity (e.g., Fergus, 1999) may seem to be problematic for the natural amenities instrument. Recall, however, that we include a measure of construction costs directly in Eq. (3), so any potential violation of the exclusion restriction must operate through correlation of the weather with *unobserved* elements of housing productivity, not construction costs *per se*.

A separate concern regarding identification is that regulatory restrictions may be endogenously correlated with unobserved supply factors. We follow Saiz (2010) in considering two instruments for regulatory restrictions. The first is the proportion of Christians in each metro area in 1971 who were adherents of "nontraditional" denominations (Johnson et al., 1974). The second is the share of local government revenues devoted to protective inspections according to the 1982 Census of Governments (of the Census, 1982). Saiz shows that these instruments predict land-use regulations in his data, as do we in ours.

To be valid instruments for land-use restrictions, these variables must also be excludable. A potential concern is the finding in Davidoff (2016) that the nontraditional Christian share is correlated with measures of housing demand growth. It is important to recall, though, that our regressions include a direct measure of metro-level land values, which ought to capitalize demand shifts. The exclusion restriction in our context is therefore that the instruments must be uncorrelated only with supply determinants in the housing sector, after controlling for construction costs. This restriction is weaker than the requirement that the instruments be uncorrelated with house prices unconditionally.

We run standard over-identification tests as a formal check on the validity of our instrumental variables, which we discuss in section 5.3. One limitation of these tests is that they require assuming at least one of the instruments is valid. Additionally, the results can be sensitive to many factors, such as the clustering of standard errors. We encourage readers to keep these limitations in mind when interpreting our results. We do believe, though, that the presence of land values and construction costs in Eq. (13) significantly strengthens the plausibility of the exclusion restrictions in our context.

5. Cost-function estimates

In this section, we estimate the cost function in Section 3.1 using the data described in Section 4 to examine how costs are influenced by geography and regulation. We restrict our analysis to metros with at least 10 land-sale observations, and years with at least 5. For our main estimates, the metros must also have available regulatory, geographic, and construction-price indices, leaving 230 metros and 1,103 metro-years. Regressions are weighted by the number of housing units in each metro.

5.1. Base OLS estimates and tests of the housing cost model

Fig. 1 plots the housing-price index, $\hat{p}_j$, against the land-value index, $\hat{r}_j$. Assuming Cobb-Douglas production and no other input cost or productivity differences, the simple regression line's slope of 0.53 would correspond to the cost share of land, ϕ. The convex gradient in the quadratic regression implies that the average cost-share of land increases with land values, yielding an imprecise estimate of $\sigma = 0.47$. The vertical distance between each metro marker and the estimated regression line forms the basis of our estimate of housing productivity. As such, Fig. 1 suggests San Francisco has low housing productivity and Las Vegas has high housing productivity.

Next we consider the construction-price index, $\hat{v}_j$, which is plotted against land values in Fig. 2. Although the two are strongly correlated,

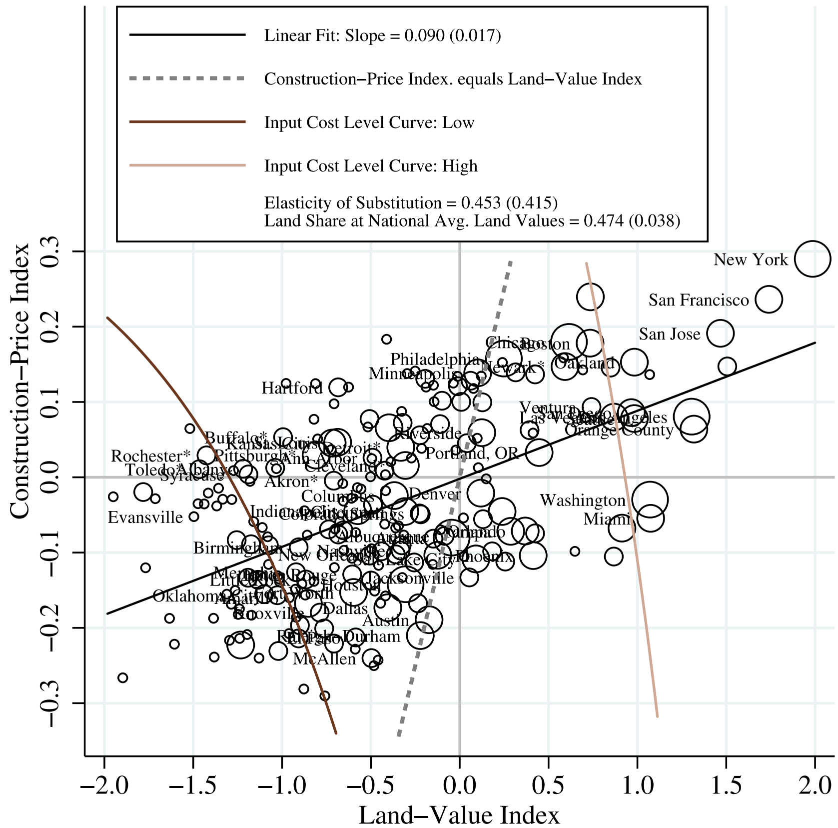


Fig. 2. Construction prices and land values, 2006–10. Note: Input cost level curves plot combinations of construction-price and land-value indices that produce housing costs 50% lower and higher than the national average holding productivity in the housing sector at the national average level. The estimated elasticity of substitution and average land share differ very slightly from Table 2, column 4, because they are estimated over time-averaged input and output prices, while the table uses measures that vary by year.

land values vary much more, and thus account for most of the variation in the land-to-construction price index $\hat{r}_j - \hat{v}_j$.[19]

Table 2 presents cost-function estimates with the aggregate geographic and regulatory indices. Columns 1 through 3 impose Cobb-Douglas production, $\sigma = 1$, as in (15); columns 1 and 2 also impose the homogeneity constraint in (14a). Column 1 is the simplest regression specification, as it excludes the restriction measures, Z_j. Including the construction index in column 1 lowers the cost share of land to 47% from 53% in the simple regression in Fig. 1. When the geographic and regulatory restriction measures are included in column 2, the estimated cost share of land falls to 36%.

Both regulatory and geographic restrictions are estimated to raise housing costs, a finding that persists throughout our analysis. The homogeneity constraint is rejected at the 5%, but not the 1%, significance level in both columns 1 and 2. The same is true of the Cobb-Douglas constraint from (15) in column 2. Column 3 relaxes the homogeneity constraint, which this raises the coefficient on the construction price but has little effect on the other estimates.

Columns 4 through 6 present parallel specifications to columns 1 through 3, but using the translog formulations (11) and (13) that allow for $\sigma \neq 1$. The cost surface shown in Fig. 3 uses the estimates without Z_j. The estimated σ there and in both columns 4 and 5 is below one-half. Importantly, the homogeneity constraints in (14a) and (14b) pass at the 5% confidence level in both columns, meaning the translog specification passes our formal statistical tests. Thus, the restricted model in column 5 provides a theoretically and empirically reasonable account of housing costs. It explains 86% of the variation across metro areas using only four variables.

Finally, the results in column 7 present estimates from the extended model with factor bias. This allows γ_2 to be non-zero in Eq. (11) by interacting the land-to-construction price index $\hat{r}_j - \hat{v}_j$ with the restrictions Z_j. The estimate of $\gamma_2 = 0.057 > 0$ for the regulatory interaction suggests that land-use regulations are biased against land. It implies a one standard deviation increase in regulation raises the cost share of land by 5.7 percentage points. Combining the value of γ_2 with the estimate that β_3 equals 0.044, Eq. (16d) implies $\delta_B = 0.65$, meaning this increase reduces the relative productivity of land by almost 50% . While suggestive, this specification fails the additional test imposed on the reduced form Eq. (13) that $\gamma_2 = -\gamma_3$.

5.2. Estimate variability and stability

Table 3 reports several exercises to gauge how the estimates change when using different data and sub-samples. All of the specifications use the constrained translog form from Eq. (11) with $\gamma_2 = 0$, corresponding to column 5 of Table 2. That specification is reproduced in column 1 of Table 3 for convenience.

Column 2 uses construction wages instead of the RS means index. The results are similar, but the homogeneity restriction is rejected. We interpret this result as suggesting that the RS Means index is a more

[19] Fig. 2 also plots estimated input cost level curves for the surface in 3. From Eq. (3), these curves satisfy $\phi\hat{r}_j + (1-\phi)\hat{v}_j + \phi(1-\phi)(1-\sigma)(\hat{r}_j - \hat{v}_j)^2 = c$ for a constant c. With the log-linearization, the slope of the level curve equals the negative ratio of the land cost share to the structural share, $-\phi_j/(1-\phi_j)$. The curve in the lower-left corresponds to a low fixed sum of housing price and productivity; the curve in the upper-right corresponds to a higher sum. The curves are concave because the estimated σ is less than one, so land's cost-share increases with its value.

Table 2
Housing cost function estimates using aggregate regulatory and geographic indices.

Specification	Constrained Cobb–Douglas (1)	Constrained Cobb–Douglas (2)	Unconstrained Cobb–Douglas (3)	Constrained translog (4)	Constrained translog (5)	Unconstrained translog (6)	Biased prod. constrained translog (7)
	Dependent variable: housing-price index						
Land-value index ϕ	0.470	0.355	0.335	0.463	0.346	0.320	0.353
	(0.039)	(0.032)	(0.038)	(0.035)	(0.032)	(0.041)	(0.025)
Construction-price index	0.530	0.645	1.038	0.537	0.654	0.946	0.647
	(0.039)	(0.032)	(0.197)	(0.035)	(0.032)	(0.200)	(0.025)
Land-value index squared				0.069	0.075	0.044	0.044
				(0.049)	(0.031)	(0.030)	(0.025)
Construction-price index squared				0.069	0.075	−1.506	0.044
				(0.049)	(0.031)	(1.975)	(0.025)
Land-value X construction-price index				−0.138	−0.150	0.337	−0.088
				(0.098)	(0.062)	(0.371)	(0.050)
Wharton regulatory index: z-score		0.069	0.065		0.081	0.083	0.088
		(0.016)	(0.018)		(0.018)	(0.018)	(0.017)
Geographic unavailability index: z-score		0.100	0.093		0.093	0.090	0.087
		(0.023)	(0.021)		(0.023)	(0.020)	(0.020)
Reg. index X land-to-construction price index							0.057
							(0.021)
Geo. index X land-to-construction price index							0.019
							(0.034)
Elasticity of substitution σ	1.000	1.000	1.000	0.444	0.333		0.616
				(0.391)	(0.263)		(0.214)
Adjusted R-squared	0.808	0.853	0.859	0.818	0.864	0.870	0.870
Number of observations	1103	1103	1103	1103	1103	1103	1103
Number of MSAs	230	230	230	230	230	230	230
p-value for homogeneity restrictions	0.010	0.041		0.083	0.286		0.153
p-value for CD constraints	0.160	0.017	0.412				
p-value for All constraints	0.002	0.007					

All regressions are estimated by ordinary least squares. Dependent variable in all regressions is the housing price index. Robust standard errors, clustered by CMSA, reported in parentheses. Data sources are described in Table 1. Restricted model specifications require that the production function exhibits homogeneity of degree one. Cobb-Douglas (CD) restrictions impose that the squared and interacted index coefficients equal zero (the elasticity of substitution between factors equals 1). All regressions include a constant term.

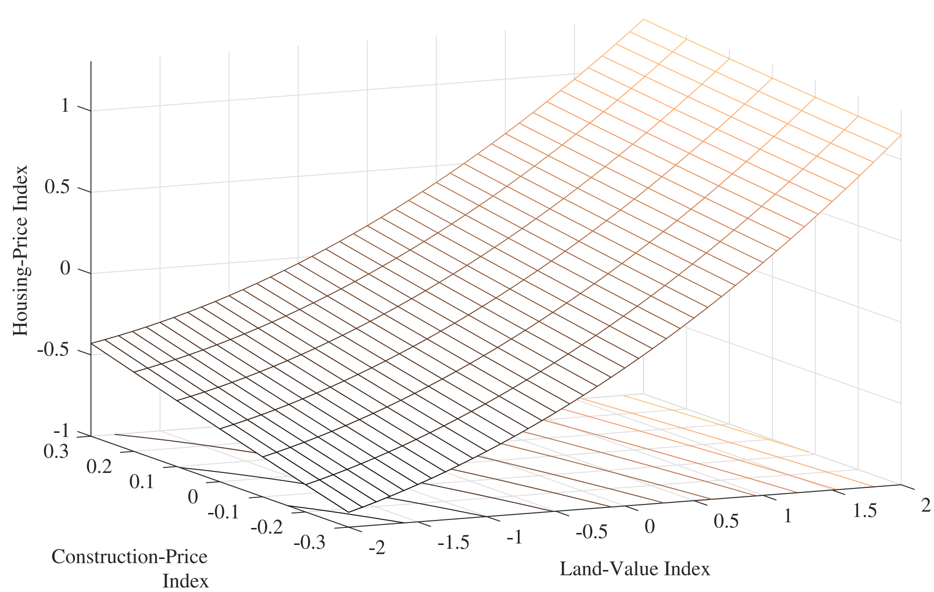


Fig. 3. Housing cost surface with $\phi = 0.47$ and $\sigma = 0.45$.

appropriate construction-price measure, likely because it also incorporates the price of non-labor inputs (i.e., materials).[20]

[20] We also estimated a three input equation that separates the structural inputs into actual materials and installation (labor) costs. Material costs vary little across space relative to these installation costs, making them difficult to use reliably. That lack of variation provides weak justification for the assumption that material costs are constant, justifying Eq. (8). Nevertheless, the Cobb-Douglas formulation produced a very similar estimate of $\phi = 0.35$ and an estimate for labor of $a(1 - \phi) = 0.39$. Interestingly, if we regress the construction wage measure on the RS means measure, we estimate $a = 0.58$, which implies a similar value for $a(1 - \phi)$.

Table 3
Constrained housing cost function estimates: sensitivity analyses.

Specification	Dependent variable: housing-price index Baseline (1)	Constr. Wages (2)	All-use land values (3)	Unwtd. land values (4)	Raw house prices (5)	2005–2007 Boom sample (6)	2008–2010 Bust sample (7)
Land-to-construction price (wage) index ϕ	0.346	0.341	0.213	0.249	0.381	0.353	0.338
	(0.032)	(0.028)	(0.024)	(0.026)	(0.040)	(0.034)	(0.032)
Land-to-construction price (wage) index squared	0.075	0.062	0.012	0.030	0.036	0.063	0.088
	(0.031)	(0.028)	(0.017)	(0.017)	(0.036)	(0.034)	(0.032)
Wharton regulatory index: z-score	0.081	0.058	0.105	0.116	0.094	0.091	0.071
	(0.018)	(0.016)	(0.018)	(0.015)	(0.02)	(0.018)	(0.019)
Geographic unavailability index: z-score	0.093	0.108	0.115	0.093	0.048	0.106	0.080
	(0.023)	(0.024)	(0.025)	(0.028)	(0.029)	(0.025)	(0.022)
Elasticity of substitution σ	0.333	0.452	0.859	0.678	0.691	0.452	0.214
	(0.263)	(0.237)	(0.211)	(0.181)	(0.294)	(0.284)	(0.264)
Adjusted R-squared	0.864	0.844	0.835	0.841	0.831	0.864	0.868

Robust standard errors, clustered by CMSA, reported in parentheses. Regressions correspond to the restricted specification in column 4 of Table 2. Column 2 replaces the construction price with wages in the construction sector. All-use land values allow for prediction adjustments based on all land uses, as explained in Albouy et al. (2018). Unweighted land values do weight census tracts by land area rather than the number of housing units. Raw house price does not control for observed housing characteristics. Building permits information is taken from City and County Data Books.

Table 4
Constrained housing cost function estimates: instrumental variables.

Specification	Dependent variable: housing-price index Cobb–Douglas (1)	Cobb–Douglas (2)	Translog (3)	Translog (4)	Translog - Limited IVs (5)	Biased translog - Limited IVs (6)
Land-to-construction price index ϕ	0.496	0.357	0.491	0.404	0.317	0.530
	(0.094)	(0.063)	(0.097)	(0.076)	(0.085)	(0.116)
Land-to-construction price index squared			0.007	0.056	0.093	0.010
			(0.086)	(0.044)	(0.038)	(0.106)
Wharton regulatory index: z-score	0.030	0.164	0.032	0.135	0.169	0.142
	(0.036)	(0.077)	(0.035)	(0.066)	(0.075)	(0.100)
Geographic unavailability index: z-score	0.061	0.080	0.062	0.063	0.085	0.055
	(0.037)	(0.027)	(0.037)	(0.028)	(0.027)	(0.041)
Reg. index X land-to-constr. price index						0.549
						(0.196)
Geo. index X land-to-constr. price index						−0.252
						(0.140)
Elasticity of substitution σ	1.000	1.000	0.942	0.535	0.137	0.917
			(0.689)	(0.365)	(0.418)	(0.850)
Adjusted R-squared	0.779	0.764	0.783	0.796	0.797	0.273
Number of observations	229	217	229	217	217	217
Instrument for land-value index?	Yes	Yes	Yes	Yes	Yes	Yes
Instrument for regulatory index?	No	Yes	No	Yes	Yes	Yes
p-value for Homogeneity restrictions	0.680	0.509	0.520	0.729	0.685	0.252
p-value of Kleibergen–Paap under-ID test	0.019	0.046	0.035	0.018	0.035	0.079
p-value of over-ID test	0.543	0.035	$<.001$	$<.001$	0.269	0.569
p-value of OLS consistency test	0.005	0.010	0.014	$<.001$	0.034	$<.001$

All regressions are estimated by two-stage least squares. Robust standard errors, clustered by CMSA, reported in parentheses. All specifications are constrained to have constant returns to scale. Columns 1 and 2 correspond to the OLS specification in Table 2, Column 2. Columns 3 through 5 correspond to the OLS specification in Table 2, Column 5. Column 6 corresponds to the OLS specification in Table 2, Column 8. In columns 1 and 3, the land-value index (and index squared) are treated as endogenous, and in the other columns the regulatory constraint index is also treated as endogenous. The instrumental variables used in columns 1 and 3 are the inverse distance to the sea, USDA natural amenities score; column 3 includes their squares and interaction. Columns 2 and 4 also include the nontraditional Christian share in 1971 and the share of local expenditures devoted to protective inspections in 1982; column 4 includes relevant interactions. Column 6 uses squares and interactions of the predicted land-value minus construction cost index and regulatory constraint index from the first-stage regressions as instruments. Tables A.2 and A.3 display all first-stage regressions. The null hypothesis of the Kleibergen-Paap test is that the model is underidentified. The overidentifying restrictions test is a J-test of the null hypothesis of instrument consistency. Test of OLS consistency is a Hausman-style test comparing consistent (IV) and efficient (OLS) specifications.

Columns 3 and 4 use two alternative land-value indices: (i) for all land uses (not just residential), and (ii) weighting land by area, not by the number of residential units. Using land for all uses in column 3 results in a smaller ϕ and a higher σ. Appendix Fig. C shows that land values for all uses vary considerably more than values for residential uses only, biasing the slope and curvature of the estimated housing cost function downwards. The results in column 4 show that weighting all land equally, ignoring where homes are located, produces similar biases.

Column 5 uses an alternative housing-price index that makes no hedonic correction for housing characteristics. The results are largely similar, if noisier. If unobserved differences in housing quality resemble observed differences, these results suggest that unobserved differences should not overturn our main conclusions.

Table 5
Estimates using disaggregate regulatory and geographic indices.

Dependent variable Specification	Reg. index Wharton regulatory index on subindices (1)	Geog. index Geographic unavail. index on subindices (2)	Hous. price Constrained translog using subindices (3)
Land-to-construction price index ϕ			0.332
			(0.029)
Land-to-construction price index squared			0.054
			(0.025)
Approval delay: z-score	0.399		0.018
	–		(0.013)
Local political pressure: z-score	0.332		0.024
	–		(0.013)
State political involvement: z-score	0.398		0.058
	–		(0.018)
Open space: z-score	0.164		−0.014
	–		(0.013)
Exactions: z-score	0.023		−0.022
	–		(0.014)
Local project approval: z-score	0.167		0.018
	–		(0.014)
Local assembly: z-score	0.124		0.014
	–		(0.008)
Density restrictions: z-score	0.194		0.018
	–		(0.015)
Supply restrictions: z-score	0.087		0.015
	–		(0.007)
State court involvement: z-score	−0.059		0.042
	–		(0.019)
Local zoning approval: z-score	−0.036		−0.009
	–		(0.011)
Flat land share: z-score		−0.491	−0.084
		(0.034)	(0.022)
Solid landshare: z-score		−0.790	−0.068
		(0.054)	(0.023)
Number of observations	1103	1103	1103
Adjusted R-squared	1.000	0.846	0.895
Elasticity of substitution σ			0.509
			(0.214)

Robust standard errors, clustered by CMSA, reported in parentheses. Regressions include constant term. Data sources are described in Table 1; constituent components of Wharton Residential Land Use Regulatory Index (WRLURI) are from Gyourko et al. (2008). Constituent components of geographical index are from Saiz (2010).

In columns 6 and 7, we split the sample into two periods: a "housing-boom" period, from 2005 to 2007, and a "housing-bust" period, from 2008 to 2010. The results are not statistically different from those in the pooled sample. The former period shows stronger effects from the restrictions, providing suggestive evidence that restrictions are more binding when housing demand is stronger.[21]

Overall, the estimates in Tables 2 and 3 support our key hypotheses: regulatory and geographic restrictions raise housing costs by 5 to 12% for a standard deviation increase in either measure. The translog model also passes tests of the homogeneity restriction in (14a) and (14b). The estimated housing cost function parameters are quite plausible, with the typical ϕ ranging from 0.32–0.36. The estimated σ is noisier and less stable, in the range of 0.3–0.6, tentatively rejecting the Cobb-Douglas hypothesis in (15).

5.3. *Instrumental variables estimates*

Table 4 presents IV estimates of the base Cobb-Douglas and translog specifications in Table 2.[22] Columns 1 and 2 present IV versions of the estimates in column 2 of Table 2.[23] Column 1 uses inverse distance from the sea and the USDA amenity score as instruments for the land-to-construction price index $(\hat{r} - \hat{v})$. Column 2 adds the nontraditional Christian share and protective inspections share as instruments, treating both the land-value and regulatory indices as endogenous.

The estimated land share in column 1 is higher than in the OLS estimates at 0.5, and a Hausman-style test rejects the null hypothesis of exogenous land values at the 5% significance level. In column 2, which instruments for both indices, the estimated land share is approximately one-third, similar to the OLS results. Instrumented increases in regulatory stringency result in substantially higher, although less precise, estimates for their efficiency costs.

Translog IV estimates in columns 3 through 5 correspond to the OLS estimates in column 5 of Table 2. Column 3 treats only land values as potentially endogenous, using the levels, squares, and interaction of the USDA amenities score and inverse distance to the sea as instruments for the $(\hat{r} - \hat{v})$ index, and its square, $(\hat{r} - \hat{v})^2$. Column 4 additionally treats the regulatory index as endogenous, using the nontraditional Christian share, the protective inspections share, and their interactions with the first two instruments as instruments. The estimated cost shares of land are again higher than in the OLS estimates in Table 2, but are also less precise. The IV estimates of the cost of land-use restrictions in column 4 are 14 log points per standard deviation, larger than in the OLS but smaller than in the IV Cobb-Douglas case. Column 5 uses a more limited set of instruments, using squares and interactions of the predicted land-to-construction price and regulatory indices from the first-stage regressions. The estimated cost share of land is closer to the OLS estimates, while the cost of regulations is higher.

[21] Minor differences may also arise from measurement error in the housing price index resulting from ACS respondents' imperfect awareness of current market conditions (Ehrlich, 2014).

[22] Appendix Tables A.1 and A.2 present first-stage estimates for all regressions in this section.

[23] Because there is no time variation in the instrumental variables, we must restrict ourselves to cross-sectional estimates in these specifications.

Table 6
Housing and trade productivity, and regulatory cost indices for selected metropolitan areas, 2005–2010.

	Housing productivity (1)	Regulatory cost index (2)	Trade productivity (Wage index) (3)
Metropolitan areas:			
Santa Cruz-Watsonville, CA	−0.902	0.095	0.177
San Francisco, CA	−0.527	0.187	0.182
San Jose, CA	−0.455	0.037	0.182
Orange County, CA	−0.437	0.060	0.080
Bergen-Passaic, NJ	−0.376	0.024	0.136
Los Angeles-Long Beach, CA	−0.385	0.121	0.080
Boston, MA-NH	−0.284	0.213	0.086
Washington, DC-MD-VA-WV	−0.035	0.047	0.119
Phoenix-Mesa, AZ	0.041	0.128	−0.002
New York, NY	0.076	0.006	0.136
Philadelphia, PA-NJ	0.088	−0.007	0.059
Chicago, IL	0.114	−0.092	0.053
Dallas, TX	0.144	−0.094	−0.002
Atlanta, GA	0.184	−0.011	−0.002
Detroit, MI*	0.165	0.031	0.002
Houston, TX	0.272	−0.071	0.017
Las Vegas, NV-AZ	0.320	−0.122	0.061
McAllen-Edinburg-Mission, TX	0.645	−0.118	−0.186
Metropolitan population:			
Less than 500,000	−0.006	−0.014	−0.055
500,000 to 1,500,000	0.020	−0.020	−0.042
1,500,000 to 5,000,000	−0.034	0.020	0.016
5,000,000+	0.012	0.005	0.073
United States	0.226	0.094	0.088
		standard deviations (population weighted)	

MSAs are ranked by inferred housing productivity. Housing productivity in column 1 is calculated from the specification in column 4 of Table 5, as the negative of the sum of the regression residual plus the housing price predicted by the WRLURI and Saiz subindices. The Regulatory Cost Index is based upon the projection of housing prices on the WRLURI subindices, and is expressed such that higher numbers indicate lower productivity. Trade productivity is calculated as 0.8 times the overall wage index.

In column 6, we push the IV strategy further to test for factor bias. This model does somewhat better at passing the over-identifying restrictions test, but at the risk of being under-identified, as evidenced by the Kleibergen–Paap statistic (Kleibergen and Paap 2006).[24] The results are qualitatively similar to those in column 8 of Table 3, suggesting that regulatory restrictions are biased against land. The estimated magnitude of the bias, as well as $\hat{\phi}$ and $\hat{\sigma}$, are even higher than in the OLS specification.

The IV estimates suggest a somewhat higher cost share of land and larger impacts of regulatory restrictions than the OLS estimates, but the IV estimates are less precise. The two bottom rows of Table 4 report the Wooldridge (1995) test of regressor endogeneity and Hansen's over-identification J-test of test of instrument exogeneity (Hansen 1982). All of the specifications formally reject the null hypothesis of regressor exogeneity, despite the substantive differences being small in several specifications. Half of the specifications reject the over-identification test of instrument exogeneity, although notably not the limited instrument specification in column 5, which features a strong first stage and results close to the OLS estimates.

The IV results largely reassure us of our OLS results. Their similar magnitudes suggest that the unobserved productivity differences, ξ_j, are relatively small after conditioning on the regulatory and geographic indices, minimizing the simultaneity and omitted-variable concerns raised in Section 3.2. As the IV specification tests are sensitive to various implementation choices, their results should be taken as suggestive, not definitive. In light of these issues and the imprecision of the IV estimates, we prefer the OLS estimates.

5.4. Calibrating alternative cost parameters

The literature on the housing cost function has offered a wide range of values for ϕ and σ. Because our main focus is on housing productivity and the costs imposed by land-use regulations, we also estimate δ_A using a wide range of cost parameters. This involves setting, or "calibrating," different values of ϕ and σ and estimating:

$$\hat{p}_j - \phi\hat{r}_j - (1-\phi)\hat{v}_j - \phi(1-\phi)(1-\sigma)(\hat{r}_j - \hat{v}_j)^2 = Z_j\delta_A + \zeta_j + \varepsilon_j$$

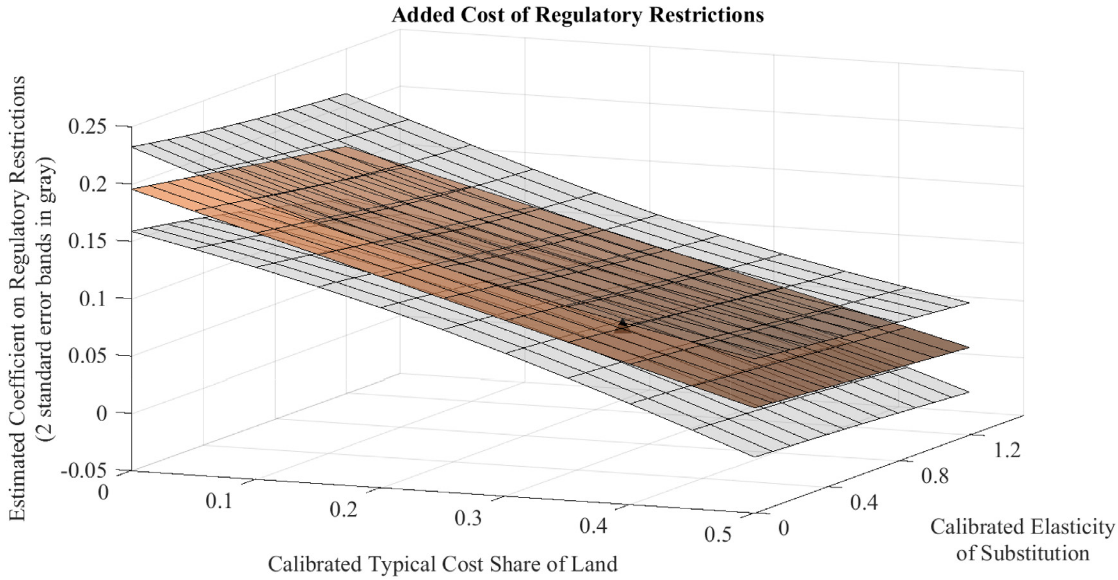
Fig. 4 shows the estimated effects using a range of ϕ from 0 to 0.5 and σ_Y from 0 to 1.2. The effects of regulation decline as ϕ rises, and the effect of geography rises slightly with σ. The point estimates suggest that both types of restrictions reduce housing productivity over the entire range of calibrated parameters, although they are not quite statistically significant at the 5% level for cost share near 0.5. Nevertheless, the finding that regulatory and geographic restrictions reduce housing productivity is generally robust to the exact shape of the housing cost function.[25]

5.5. Disaggregate indices and the regulatory cost index

We next consider which types of land-use restrictions do the most to increase housing costs. The Wharton index aggregates 11 subindices, while the unavailability index aggregates two. Column 1 of Table 5 presents descriptive coefficient estimates from a regression of the aggregate WRLURI z−score on the z−scores for the subindices. Column 2 presents similar estimates for the Saiz subindices, which are

[24] The null hypothesis in the Kleibergen-Paap test is that the model is under-identified, so failing to reject the null hypothesis is potential evidence of weak instruments.

[25] Appendix table A3 presents a similar sensitivity analysis for fewer parameter combinations in the instrumental variable context. The same qualitative patterns hold for the IV analysis.



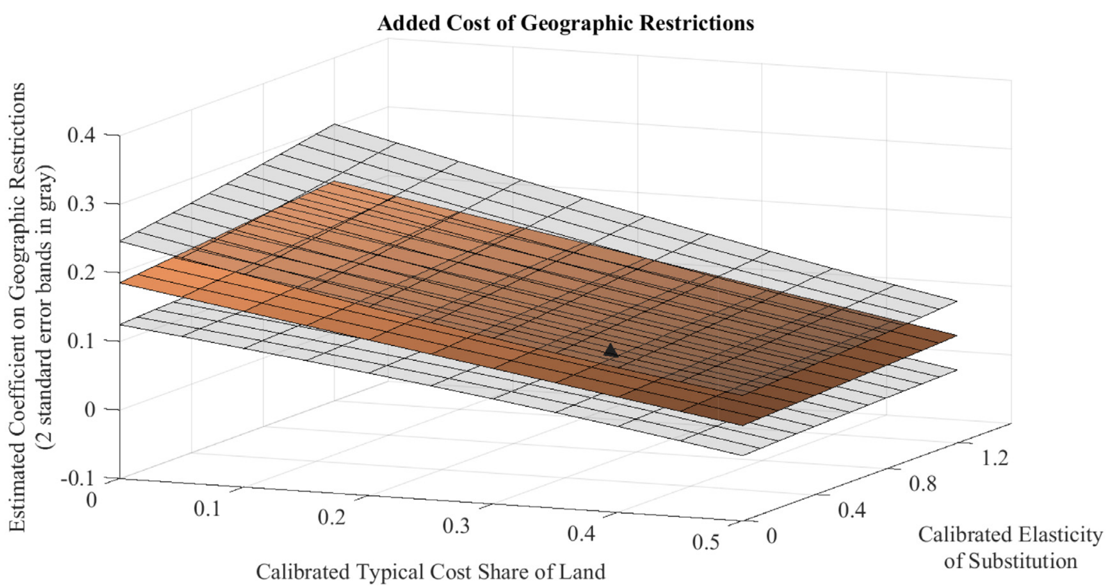


Fig. 4. Estimated effects of restrictions on housing productivity using a calibrated cost function. Note: Solid surfaces show estimated effects of regulatory and geographic restrictions on housing costs for various cost shares of land and elasticities of substitution. Translucent surfaces show estimated two standard error bands. Black triangles show OLS estimates of effects of restrictions at estimated cost share and elasticity of substitution using constrained translog cost function in column 2 of table 5.

negative because the subindices indicate land that may be available for development.

The key estimates in this table are in column 3, which features the disaggregated regulatory and geographic subindices in our favored restricted translog specification. The estimates of $\phi = 0.332$ and $\sigma = 0.51$ are close to our estimates in column 5 from Table 2. These small changes from moving to a richer model suggest that the biases from unobserved housing-productivity determinants ζ_j are likely to be minor.

The disaggregated results indicate that one-standard deviation increases in state political and state court involvement reduce metro-level productivity by 6 and 4 percentage points, while local supply restrictions raise costs by 1.5 percentage points. Those estimates are significant at the 5% level; at the 10% significance level, local political pressure raises costs by 2.4 percentage points. The one marginally significant negative coefficient is on exactions (also known as "impact fees"). This result is suggestive because exactions are thought to be a relatively efficient land-use regulation, especially when they help pay for infrastructure improvements (Yinger, 1998).

The regression coefficients are positively related to the coefficients in column 1, but they put relatively more weight on state restrictions than on local ones. This is consistent with results in Glaeser and Ward (2009) that more local regulations have limited effects on prices, so long as housing consumers have substitute communities nearby where builders are not constrained.

One caveat to these results is that, in theory, different types of land-use regulations should have different effects on land and house prices. Brueckner (1999) shows that restrictions that reduce the supply of developable land without otherwise affecting the development process should increase land prices without shifting the production and cost functions. Our framework is arguably less well-suited to these sorts of restrictions, which may be captured by the Open Space and Supply Restrictions subindices. The (insignificant) negative coefficient on the open space

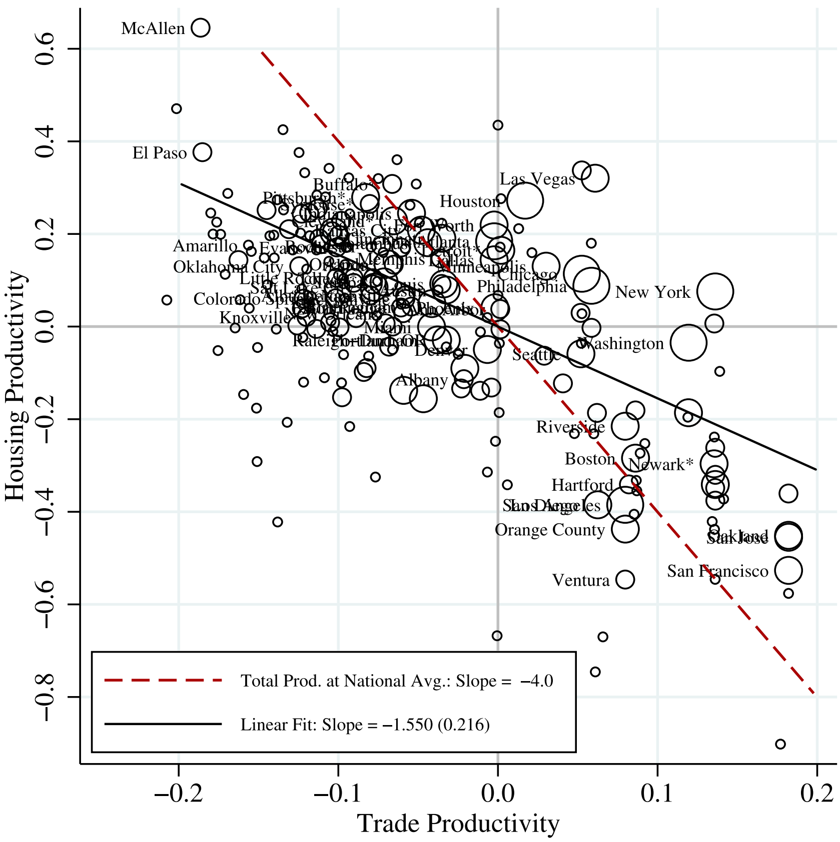


Fig. 5. Productivity in the traded and housing sectors.

index is consistent with this argument, although the positive coefficient on the supply restrictions index is less so. Of course, given the difficulties of measuring regulations, as well as the high multicollinearity between the various subindices, we caution against taking any one estimate too literally.

We use the estimates in column 3 of Table 5 to construct a cardinal estimate of the economic costs of land-use regulations, which we call the "Regulatory Cost Index" (RCI). Partitioning the coefficient vectors into the regulatory and the geographic, γ^R and γ^G, the RCI is given by the predicted value $Z_j^R\hat{\gamma}^R$. It is worth noting how the weights on the RCI in column 3 differ in relative magnitude from those in column 1.

The coefficients on both of the Saiz subindices have statistically and economically significant negative point estimates, indicating a one standard-deviation increase in the share of solid or flat land is associated with a 7 and 8% reduction in housing costs, respectively.[26]

From the cost-share approximation in Section 2, the cost share of land ranges from 6% in Jamestown, NY to 50% in New York City. The partial elasticities of housing supply, η_j, range from 0.5 at the first percentile to 3.0 at the 99th percentile. Interestingly, a 1-point increase in our estimated elasticity predicts a 1.05-point (s.e. = 0.15) in the elasticity estimated by Saiz (2010).

6. Housing productivity across metropolitan areas

6.1. Productivity in housing and tradeables

Column 1 of Table 6 lists our most inclusive measure of housing productivity, including both observed and unobserved components (i.e., $\hat{A}_j^Y = -Z_j\hat{\gamma}_1 - \hat{\zeta}_j$), for both regulations and geography, and assuming no error ($\varepsilon_j = 0$). Thus, McAllen, TX has the most productive housing sector, while Santa Cruz, CA has the least. Among metros with over one million inhabitants, the top five—excluding our low-growth sample—are Las Vegas, Houston, Indianapolis, Fort Worth, and Kansas City; the bottom five are San Francisco, San Jose, Oakland, Orange County, and San Diego.[27]

Column 2 reports our RCI, which is based only on the productivity loss predicted by the regulatory subindices, $Z_j^R\hat{\gamma}_1^R$. The cities with the highest regulatory costs are in New England, notably Manchester, NH; Brockton, MA; and Lawrence, MA-NH. The regulations in Boston, which tops the list of most regulated large cities, predict 30% higher costs than in Chicago. The West South Central regions contains the cities with the lowest RCI: New Orleans, LA; Lake Charles, LA; and Little Rock, AR. Column 3 provides a comparable measure of trade productivity, following Eq. (6), using wages outside of the construction sector and a cost share of $\theta_N = 0.85$.[28]

Fig. 5 plots housing productivity relative to trade productivity. An interesting result in the figure is that trade productivity and housing productivity are negatively correlated: a 1-point increase in trade productivity predicts a 1.6-point decrease in housing productivity. Coastal cities in California have among the highest levels of trade productivity and the lowest levels of housing productivity. In contrast, cities such as Dallas and Atlanta are relatively more productive in housing than in tradeables. The figure includes a level curve for total productivity $\hat{A}_j^{TOT} = s^X\hat{A}_j^X + s^Y\hat{A}_j^Y$, which has a slope of $-s^X/s^Y$.

[26] In appendix Table A.4, we also consider how these specific variables may contribute to factor bias. Including so many variables pushes the data to its limits. The most significant results imply that local project approval and supply restrictions are biased against land. Meanwhile, flat and solid land both appear to reduce the bias against land.

[27] See appendix Table A.5 for the values of the major indices and measures for all of the metros in our sample.

[28] This follows Albouy (2016) except that we exclude a small component from land used by firms in the traded sector, which we leave for future work.

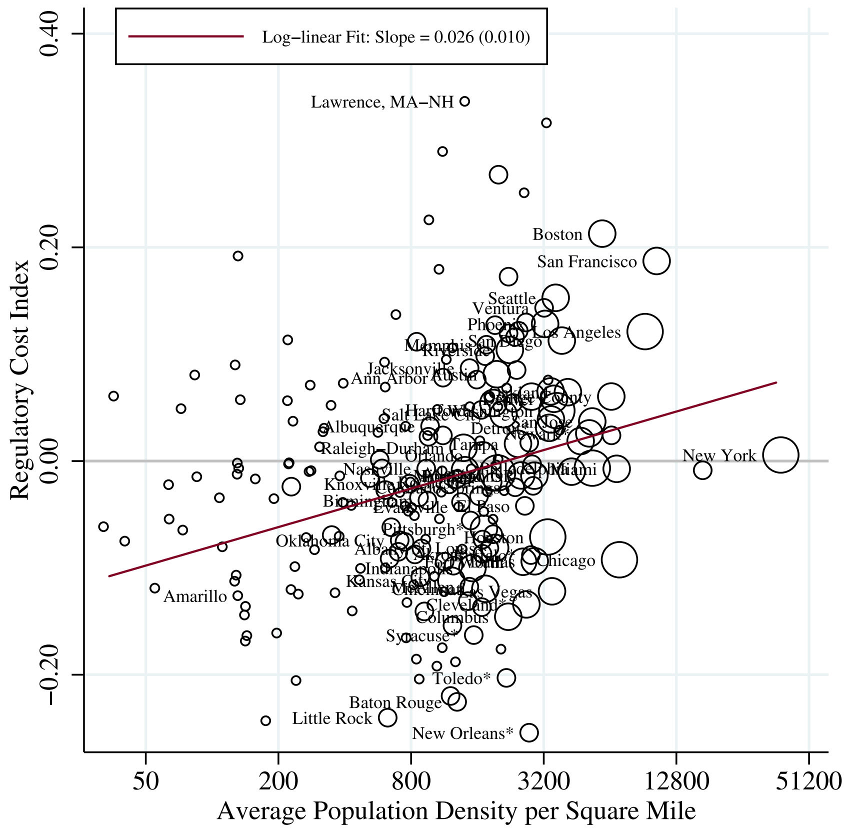


Fig. 6. The regulatory cost index and population density.

6.2. Productivity-population gradients in housing

Part of the negative estimated correlation between trade and housing productivity estimates is related to city size. As in Rosenthal and Strange (2004), economies of scale in traded goods increase with city size. Urban economies of scale in housing production, however, seem to decrease.

This relationship may arise from technical difficulties in producing housing in crowded, developed areas. Additionally, new construction and renovations impose negative externalities on incumbent residents. Noise, dust, and safety hazards are greater nuisances in denser environments. Local residents often protest new developments over fears of permanent negative externalities from greater traffic or blocked views (Glaeser et al., 2005a). These fears of negative externalities can cause incumbent residents in populous areas to regulate new development, raising housing costs. Fig. 6 illustrates this idea by plotting the RCI relative to population density. The two are positively correlated.

Table 7 examines the relationship of productivity with population levels, aggregated at the consolidated metropolitan (CMSA) level, in panel A, and population density, in panel B. In column 1, the positive elasticities of trade productivity with respect to population and density of 5.2 and 5.5% are consistent with many in the literature (Ciccone and Hall 1996, Melo et al. 2009). When trade productivity $\hat{A}_j^X$ is weighted by its expenditure share, $s^X = 0.64$, in column 4, these elasticities are 3.3 and 3.5%.

Column 2 indicates negative elasticities of housing productivity with respect to population of 6.3 and 5.4%. We weight this using a conservative expenditure share on housing of $s^Y = 0.16$ in column 5, which results in estimated diseconomies of negative 1%.[29] Added together, the implied total economies of scale in production are reduced to elasticities of 2–3% on net for both population and density.

Column 3 shows elasticities with respect to the negative of the RCI (the negative is used because a higher RCI reduces housing productivity). The results are smaller but still substantial: a 10% increase in population engenders regulations that raise housing costs by roughly 0.25%. Weighted by the housing expenditure share, regulations lower the income-population and density gradients for total productivity by about 0.4 percentage points, eliminating about one-eighth of urban productivity gains.

7. Housing productivity and quality of life

7.1. Do land-use restrictions increase housing demand?

Even if land-use regulations drive up the cost of housing, they may also increase local quality of life by "recogniz[ing] local externalities, providing amenities that make communities more attractive" (Quigley and Rosenthal, 2005). In this manner, regulation raises house prices by increasing demand, rather than by limiting supply. Moreover, so-called "fiscal zoning" may be used to preserve the local property tax base and deliver public goods more efficiently, in support of the Tiebout (1956) hypothesis (Hamilton, 1975; Brueckner, 1981). To our knowledge, there are only a few estimates of the net welfare benefits of land-use regulations, e.g., Cheshire and Sheppard (2002), Glaeser et al. (2005a), and Waights (2015), all of which suggest low benefits.

To examine this hypothesis across U.S. cities, we first estimate how housing productivity relates to quality of life. The quality of life

[29] That proportion uses a narrow definition of housing and a broad measure of expenditures. In other work (Albouy et al., 2016a), we use a broader definition of housing and a more narrow definition of expenditures, resulting in s^Y above 0.22.

Table 7
Urban economies and diseconomies of scale.

Dependent Variable	Trade productivity (1)	Housing productivity (2)	Minus regulatory cost index (-RCI) (3)	Productivities weighted by income share: Trade only (4)	Housing only (5)	Total: trade and housing (6)	Total: trade and housing (RCI Only) (7)
Panel A: Population							
Log of Population	0.052	−0.063	−0.025	0.033	−0.011	0.023	0.029
	(0.004)	(0.021)	(0.007)	(0.003)	(0.004)	(0.004)	(0.003)
Adjusted R-squared	0.653	0.145	0.116	0.653	0.145	0.502	0.618
Panel B: Population Density							
Weighted Log Pop. Density	0.055	−0.054	−0.026	0.035	−0.010	0.027	0.031
	(0.004)	(0.026)	(0.009)	(0.003)	(0.005)	(0.004)	(0.002)
Adjusted R-squared	0.386	0.053	0.066	0.386	0.053	0.349	0.366
Number of observations	230	230	230	230	230	230	230

Robust standard errors, clustered by CMSA, reported in parentheses. Trade and housing productivity indices and regulatory cost index are calculated as in Table 6. Weighted productivities in columns (4) and (5) are weighted by the housing share, 0.16, and the traded share, 0.64, respectively. Total productivity in column (6) is calculated as 0.16 times housing productivity plus 0.64 times trade productivity. Weighted density index is calculated as the population density at the census-tract level, weighted by population. Total productivity (RCI Only) in column 7 is defined as the traded goods share, 0.64, times trade productivity minus the housing share, 0.16, times the Regulatory Cost Index.

Table 8
The welfare consequences of land-use regulation.

Amenity controls	None (1)	Nat. (2)	Nat. & Art. (3)	None (4)	Nat. (5)	Nat. & Art. (6)
Panel A			Dependent variable: quality of life			
Total housing productivity	−0.25	0.01	0.04			
	(0.04)	(0.03)	(0.04)			
Minus regulatory cost index (RCI)				−0.46	−0.04	0.05
				(0.10)	(0.04)	(0.04)
Adjusted R-squared	0.36	0.75	0.85	0.22	0.75	0.85
Housing share of consumption (Direct benefit)	0.16	0.16	0.16	0.16	0.16	0.16
Elasticity of social welfare with respect to Increasing housing productivity/Reducing RCI	−0.09	0.17	0.20	−0.30	0.12	0.21
Panel B			Dependent variable: land value			
Total housing productivity	−1.72	0.29	0.62			
	(0.33)	(0.25)	(0.28)			
Minus regulatory cost index (RCI)				-3.74	−0.86	0.26
				(0.89)	(0.48)	(0.41)
Adjusted R-squared	0.23	0.60	0.83	0.20	0.61	0.83
Controls for natural amenities		X	X		X	X
Controls for artificial amenities			X			X
Number of observations	230	225	216	230	225	216

Robust standard errors, clustered by CMSA, in parentheses. Regulatory cost index presented in Table 6. Natural controls: quadratics in heating and cooling degree days, July humidity, annual sunshine, annual precipitation, adjacency to sea or lake, log inverse distance to sea, geographic constraint index, and average slope. Artificial controls include eating and drinking establishments and employment, violent crime rate, non-violent crime rate, median air quality index, teacher-student ratio, and fractions with a college degree, some college, and high-school degree. Both sets of controls are from Albouy et al. (2016b) and Albouy (2016). Elasticity of Social Welfare is calculated as expenditure share of housing, 0.18, plus elasticity of Willingness-to-Pay with respect to Housing Productivity or minus RCI.

estimates are based on willingness-to-pay measures derived from Eq. (6).[30] Fig. 7 and panel A of Table 8 show the relationship between quality of life and the RCI without any controls. The simple regression line in the figure suggests that a one-point increase in housing productivity is associated with a 0.25-point decrease in quality of life (also shown in column 1). Column 4 of Table 8 implies that a one-point increase in regulatory costs is associated with a 0.46-point increase in quality of life.[31]

There are serious problems with interpreting these raw correlations as causal. First, they ignore the likelihood that areas with higher quality

[30] The derivation follows Albouy (2008) with some adjustments. We use an expenditure share of 0.16 for housing, and 0.64 for traded goods. The expenditure share is 0.2 for remaining non-housing non-traded goods. We use $\hat{p}_j + \hat{A}_j^Y$ as the price of this non-traded good to reflect input costs because we do not estimate local productivity in that sector. This approach also minimizes problems of division bias. The value of $t = 0.72$ we use implies a value of $a(1-\phi) = 0.4$, which is consistent with the disaggregated analysis discussed above. To account for federal taxes on labor (Albouy, 2009), wage differences are reduced by a third; for tax benefits to owner-occupied housing, housing price differences are reduced by one-sixth. We use only aggregate estimates of $\hat{Q}_j$: $\hat{Q}_j^X$ and $\hat{Q}_j^Y$ have a correlation of 0.91.

[31] The coefficients on housing productivity and the RCI in quality-of-life regressions will tend to have opposite signs because higher values of $\hat{A}_j^Y$ denote more efficient housing production and higher values of the RCI indicate more costly regulations.

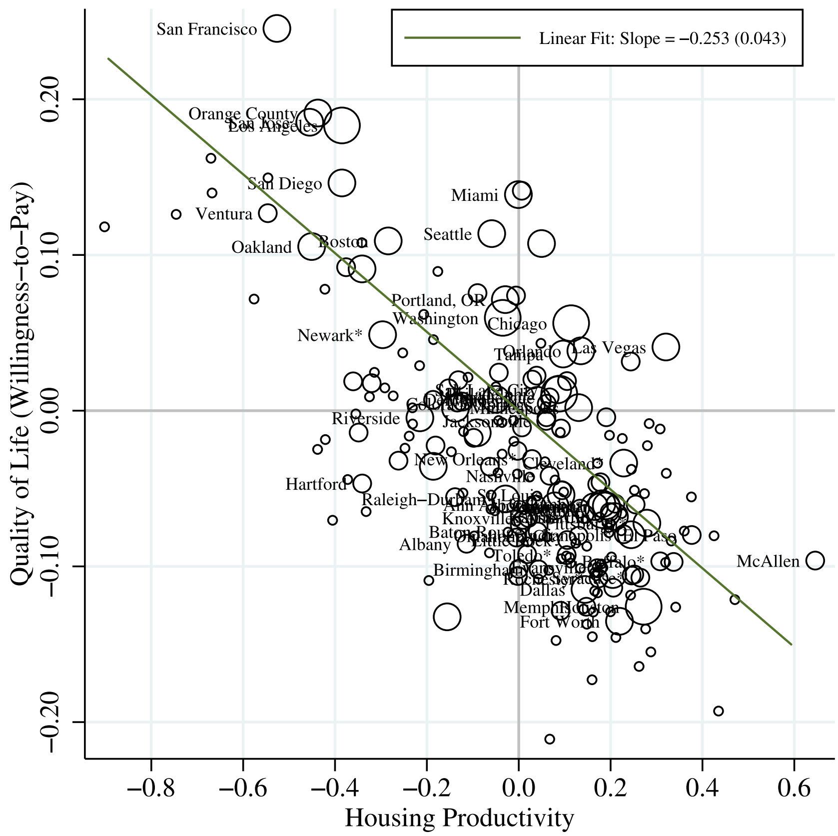


Fig. 7. The uni-variate relationship of quality of life and housing productivity.

of life may be more prone to regulate. This problem motivates controlling for observable amenities that predict quality of life. Second, the correlations suffer from a potential "division bias": housing productivity is inferred in part from low prices, while quality of life is inferred in part from high prices. Therefore, any measurement error will automatically create a negative bias in the estimated relationship.

To control for observable amenities, we estimate the following equation:

$$\hat{Q}_j \equiv s^Y \hat{p}_j - t\hat{w}_j = \hat{A}_j^{Y*} a + \sum_k q_j^k b_k + e_j \tag{17}$$

where q_j^k refers to individual amenities. The coefficient a represents the elasticity of households' willingness to pay for housing productivity as a fraction of their incomes. To focus on changes in productivity due to regulations, we replace $\hat{A}^{Y*}$ with $-RCI_j^*$.

Controlling for observable amenities changes the estimated relationship dramatically. Columns 2 and 5 include controls for natural amenities, such as climate, adjacency to the coast, and the geographic restriction index. These presumably exogenous controls virtually eliminate the estimated correlations between quality of life and housing productivity or regulatory costs. For example, we estimate that Boston has a higher quality of life than Chicago. However, after controlling for natural amenities, willingness-to-pay to live in Chicago is actually higher than in Boston, despite the fact that Chicago's land use is much less regulated.

Columns 3 and 6 add controls for artificial amenities such as the population level, density, education, crime rates, and number of eating and drinking establishments of each metro area. Including these controls suggests that land-use restrictions could actually lower quality of life, albeit insignificantly. Overall, the effect of regulations on housing demand is confounded by local amenities: while attractive places tend to restrict land use, restricting land use does not obviously make a place more attractive.[32]

7.2. Net effects on welfare and land values

To determine land use restrictions' net effects on welfare, we again posit a conservative share of expenditures on housing of $s^Y = 0.16$. Thus, the social cost of land-use restrictions, expressed as a fraction of total consumption, are to a first-order approximation an average of 0.16 times the RCI. For quality-of-life benefits to exceed this cost, the elasticity of quality of life with respect to the RCI, estimated in a, must exceed this share. That is, the net costs of land-use regulations are equal to $s^Y + a$.

If we were naively to accept the simple regression relationship in column 4 of Table 8, panel A, as causal, the benefits of regulation would appear to outweigh their costs as $s^Y + a = -0.09$. As discussed above, the regulatory environment is highly correlated with local amenities that

[32] The quality of life estimates reflect values that are exhibited on the market. Regulations may produce idiosyncratic values for local residents that are not valued externally by the marginal buyer. For example, a majority of incumbent residents in a community may prefer a low residential density. If outside buyers, who represent the majority of the outside market, care nothing for low densities, this will not show up in higher housing (and land) prices or in willingness-to-pay measures. Idiosyncratic benefits are also related to how preference heterogeneity impacts the willingness-to-pay used to estimate quality of life benefits. Limiting the number of residents can raise the willingness to pay of the marginal resident through ω_{ij}, without producing actual benefits in $\hat{Q}_{0j}$. This issue is most problematic if land-use restrictions reduce the supply of housing by reducing land supply. With homogeneous preferences, simply removing land from development on this "extensive" margin should not impact prices in a small open city: land supply does not enter Eq. (9d). If preferences are heterogeneous, reducing land supply will lower the number of residents in a community, raising willingness-to-pay, similar to the model of Gyourko et al. (2013).

households value. Controlling for amenities in columns 5 and 6 renders the positive effects of regulation on quality of life too small economically to outweigh their costs. The estimates in columns 5 and 6 imply an elasticity of social welfare with respect to the RCI of negative 0.1–0.2, meaning regulations that lower housing productivity also reduce social welfare.

Welfare-reducing regulations may persist through inefficient local politics due to insider-outsider dynamics. Suppose that voters in a community consist mainly of property owners or renters subject to rent control. These community "insiders" are not harmed by regulations that raise housing costs as long as they do not wish to move locally. Those costs are borne instead by potential residents, community "outsiders," who must purchase a new house or rent at the market rate. These outsiders cannot vote in the communities they would like to move to beforehand. If land-use restrictions produce quality-of-life benefits, however small or idiosyncratic, they may be supported by local voters.[33] As our results are at the metropolitan level, they could point to a Coasean failure. Potential residents or developers may lack the coordination to buy out incumbents, leading to aggregate inefficiency.

We conclude in panel B of Table 8 by considering the overall effects of productivity and regulations on local land values. This involves running a regression of the form (17), except with $\hat{r}_j$, instead of $\hat{Q}_j$, as the dependent variable. The net welfare loss from regulations implies that they should lower land values despite increasing house prices.[34]

The simple regressions in columns 1 and 4 reveal that land values are negatively related to housing productivity and even more strongly positively related to the RCI. Again, this correlation may be confounded by local amenities. In addition, as we saw earlier, places with lower housing productivity have higher trade productivity, which also raises land values. As such, higher housing productivity or a lower RCI do not appear to raise land values after controlling for natural amenities. Adding controls for artificial amenities in columns 3 and 6 provides some provisional evidence of that land-use restrictions may reduce land values.

8. Conclusion

Our approach takes advantage of the large inter-metropolitan variation in land values, construction prices, and regulatory and geographic restrictions to estimate a cost function for housing in the United States. By separating input and output prices for housing, our approach isolates how land-use restrictions affect housing prices through supply and demand channels. Despite our disparate data sources, the estimated cost function fits the data well, and the estimates have credible economic magnitudes.

The evidence supports the hypothesis that regulatory and geographic restrictions create a wedge between the prices of housing and its inputs. Sensitivity checks, instrumental variable methods, and calibration exercises support this conclusion. Disaggregated measures suggest that state political and court involvement are associated with large increases in housing costs. Our new Regulatory Cost Index quantifies the economic cost of housing regulations, purged of demand factors, which we hope will be useful to other researchers.

The observed price gradients imply an average cost share of land in housing near one-third and that substitution between land and nonland inputs is inelastic, although our estimates regarding regulatory and geographic restrictions appear to hold over a wide range of housing-cost parameters. During our study period, land's cost share ranged from 6 to 50% across U.S. metro areas. These varying cost shares provide an intuitive explanation for why the price elasticities of housing supply differ across cities.

A key result is that large cities tend to be less productive in the housing sector, while more productive in traded sectors. These two productivities seem to be subject to opposite economies of urban scale. Much of the urban scale diseconomy in housing is attributable to larger cities being more regulated.

While some land-use restrictions may enhance welfare, overall the regulations measured here have little positive impact on local quality of life after controlling for standard observable amenities. For example, potential residents do not find Chicago less desirable than Boston because it is less regulated, but they do benefit from Chicago's higher housing productivity. Thus, land-use regulations appear to raise housing costs more by restricting supply than by increasing demand. On net, the typical land-use regulation in the United States reduces well-being by making housing production less efficient and housing consumption less affordable.

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Appendix A. Housing productivity and factor bias

Consider the case in which housing productivity is factor specific. Suppressing the superscript Y, the production function for housing is $Y_j = F(L, M; A_j, B_j) = F(A_j^L L, A_j^M M; 1)$. Further consider the case of Hicks-neutral (total factor) productivity so that $A_j^L = A_j^M = A_j$. The biases are captured by the ratio $B_j^Y = A_j^L / A_j^M$. It is convenient to express these in the log-linear case as $\hat{A}_j \equiv \phi \hat{A}_j^L + (1-\phi)\hat{A}_j^M$ and $\hat{B}_j \equiv \hat{A}_j^L - \hat{A}_j^M$.

For exposition, consider efficiency units of land and materials, $L^* \equiv A_j^L L$, $M^* \equiv A_j^M M$. The prices of these efficiency units are $\tilde{r} \equiv r/A^L$, $v^* = v/A^M$. Further, drop the subscripts on the prices. Because $rL + vM = r^* L^* + v^* M^*$, an equivalent cost function can be written as

$$C^*\left(r^*, v^*, Y\right) \equiv \min_{L^*, M^*} \left\{ r^* L^* + v^* M^* \, : \, F\left(L^*, M^*\right) = Y \right\} \tag{A.1}$$

Because of constant returns to scale, the unit cost function is then

$$c^*\left(r^*, v^*\right) \equiv \min_{l^*, m^*} \left\{ r^* l^* + v^* m^* \, : \, F\left(l^*, m^*\right) = 1 \right\} \tag{A.2}$$

where $l \equiv L/Y$ and $m \equiv M/Y$ are input-output ratios. According to Shephard's Lemma, the first derivatives of the cost function with respect to the first and second arguments are written

$$c_r^* \equiv \frac{\partial c^*}{\partial r^*} = l^* = \frac{L^*}{Y}, \quad c_v^* \equiv \frac{\partial c^*}{\partial v^*} = m^* = \frac{M^*}{Y} \tag{A.3}$$

Taking the logarithm of the cost function, and then the first derivatives:

$$\frac{\partial \ln c^*}{\partial \ln r^*} = \frac{c_r^* r^*}{c^*} = \frac{rL}{cY} = \phi, \quad \frac{\partial \ln c^*}{\partial \ln v^*} = \frac{c_v^* v^*}{c^*} = \frac{vM}{cY} = 1 - \phi \tag{A.4}$$

[33] See Lindbeck and Snower (2017) for a model of insider-outsider dynamics. Levine (2005) examines how U.S. courts consider have ignored costs placed on outsiders from land-use restrictions.

[34] This prediction is subject to the caveat noted in Brueckner (1999) that policies that limit the extensive margin of land supply can actually raise the price of developable land, by limiting population and raising the willingness to pay of the marginal resident.

where the last line follows from factor exhaustion. Assuming the equilibrium condition $\ln p = \ln c = \ln c^*$ holds, then we have the first-order approximation:

$$\hat{p}_j = \phi\hat{r}^* + (1-\phi)\hat{v}^* = \phi\hat{r}_j + (1-\phi)\hat{v}_j \underbrace{-\phi\hat{A}^L_j - (1-\phi)\hat{A}^M_j}_{-\hat{A}^Y_j} \tag{A.5}$$

The first-order approximation is Cobb–Douglas, and does not allow us to disentangle factor bias as both $\hat{A}^L_j$ and $\hat{A}^M_j$ are only in the residual. To consider factor bias, we need the second derivatives. Because of Young's Theorem, only a single mixed derivative is needed

$$\frac{\partial^2 \ln c^*}{\partial \ln r^* \partial \ln v^*} = \frac{c^*_r r^*}{c^*}\left(\frac{v c_{rv}}{c^*_r} - \frac{v c^*_v}{c}\right) = -\phi(1-\phi)(1-\sigma) \tag{A.6}$$

The mixed derivative is the negative of the second-order pure derivatives, which are equal due to symmetry:

$$\frac{\partial^2 \ln c^*}{\partial^2 \ln r^*} = \frac{c^*_r r^*}{c^*}\left(1 - \frac{c^*_r r^*}{c^*} - \frac{c^*_{rr} r^*}{c^*_r}\right) = \phi(1-\phi)(1-\sigma) = \frac{\partial^2 \ln c^*}{\partial^2 \ln v^*}. \tag{A.7}$$

The second-order pure derivatives are the first-order derivatives of the function describing the cost shares. How the cost-share, ϕ_j, should vary over cities, can be derived directly by taking a first-order Taylor expansion of it in its arguments r^* and v^*.[35] This yields:

$$\phi_j = \phi + \phi(1-\phi)(1-\sigma)(\hat{r}_j - \hat{v}_j + \underbrace{\hat{A}^M_j - \hat{A}^L_j}_{-\hat{B}_j}) \tag{A.8}$$

which is Eq. (4) in the main text. When $\sigma = 1$, the cost share is constant across cities. If $\sigma < 1$, the cost share of land rises with the relative price of land and falls with its relative productivity. Thus, a factor bias against land raises its cost share.

The symmetry between the pure and mixed partial derivatives leads to the following second-order log-linear approximation of the cost function:

$$\begin{aligned}\hat{c}_j &= \phi(\hat{r}_j - \hat{A}^L_j) + (1-\phi)(\hat{v}_j - \hat{A}^L_j)\\ &+ (1/2)\phi(1-\phi)(1-\sigma)(\hat{r}_j - \hat{v}_j - \hat{A}^L_j + \hat{A}^M_j)^2\\ &= \phi\hat{r}_j + (1-\phi)\hat{v}_j + (1/2)\phi(1-\phi)(1-\sigma)(\hat{r}_j - \hat{v}_j - \hat{B}_j)^2 + \hat{A}_j,\end{aligned}$$

which provides the formulation in Eq. (3) in the main text.

Productivity and bias are not observed directly, but must be inferred. We write overall productivity and factor bias as linear functions of a vector of restrictions Z:

$$\hat{A}_j = -Z_j\delta_A - \xi_{Aj} \tag{A.9a}$$

$$\hat{B}_j = -Z_j\delta_B - \xi_{Bj} \tag{A.9b}$$

The linear terms in $Z_j\delta$ account for the (linear) observed components of total productivity and factor biases; the ξ_j terms account for the unobserved components or non-linearities.

Substituting in these expressions, multiplying out the quadratic term, and subtracting the construction price index, creates the series of terms:

$$\hat{p}_j - \hat{v}_j = \phi(\hat{r}_j - \hat{v}_j) \tag{A.10a}$$

$$+ (1/2)\phi(1-\phi)(1-\sigma)(\hat{r}_j - \hat{v}_j)^2 \tag{A.10b}$$

$$+ Z_j\delta_A \tag{A.10c}$$

$$+ \xi_{Aj} \tag{A.10d}$$

$$+ \phi(1-\phi)(1-\sigma)(\hat{r}_j - \hat{v}_j)Z_j\delta_B \tag{A.10e}$$

$$+ (1/2)\phi(1-\phi)(1-\sigma)(Z_j\delta_B)^2 \tag{A.10f}$$

$$+ \xi_{Bj}\phi(1-\phi)(1-\sigma)(Z_j\delta_B + \hat{r}_j - \hat{v}_j + \xi_{Bj}/2) \tag{A.10g}$$

The first four lines describe the main productivity model. The term on line (A.10a) identifies the cost-share terms from log-linear price differences. The term on the second line, (A.10b), identifies the elasticity of substitution from the square of log-linear price differences. The third term, (A.10c) gives the observed productivity effect, while the fourth, (A.10d) gives the unobserved component.

The last three lines account for factor bias. The term (A.10e) estimates factor bias in δ_B through the interaction of the observable shifters Z_j, and the price difference, $\hat{r}_j - \hat{v}_j$. The term (A.10f) provides an alternative method of estimating factor bias that relies on the linearity imposed in (A.9a) and (A.9b). However, it is unlikely that the relationships are truly linear. Moreover, Z lacks the cardinal properties of the price indices, $\hat{r}_j$ and $\hat{v}_j$. Thus, we group it and the remaining terms in an error term along with (A.10g).

Based on the above discussion, we collect the coefficients as

$$\beta_1 = \phi$$
$$\beta_3 = (1/2)\phi(1-\phi)(1-\sigma)$$
$$\gamma_1 = \delta_A$$
$$\gamma_2 = \phi(1-\phi)(1-\sigma)\delta_B = 2\beta_3\delta_B$$

to create a reduced-form equation that contains all of the structural constraints:

$$\hat{p}_j - \hat{v}_j = \beta_1(\hat{r}_j - \hat{v}_j) + \beta_3(\hat{r}_j - \hat{v}_j)^2 + \gamma_1 Z_j + \gamma_2 Z_j(\hat{r}_j - \hat{v}_j) + \zeta_j + \varepsilon_j \tag{A.11}$$

where the error term consist of two components: the first component is driven mainly by unobservable determinants of productivity and bias,

$$\zeta_j = \xi_{Aj} + \xi_{Bj}\phi(1-\phi)(1-\sigma)(Z_j\delta_B + \hat{r}_j - \hat{v}_j + \xi_{Bj}/2 + (Z_j\delta_B)^2/2). \tag{A.12}$$

The second component, ε_j, captures sampling, specification, and measurement error in the price index. The ζ_j component must be heteroskedastic unless $\delta_B = \xi_{Bj} = 0$, in which case $\zeta_j = \xi_{Aj}$.

The constrained reduced-form equation is embedded inside of a more general unconstrained equation:

$$\begin{aligned}\hat{p}_j &= \beta_1\hat{r}_j + \beta_2\hat{v}_j + \beta_3(\hat{r}_j)^2 + \beta_4(\hat{v}_j)^2 + \beta_5(\hat{r}_j\hat{v}_j) + \gamma_1 Z_j\\ &+ \gamma_2 Z_j\hat{r}_j + \gamma_3 Z_j\hat{v}_j + \varepsilon'_j\end{aligned} \tag{A.13}$$

The constrained model then imposes the following four testable constraints on the coefficients in (A.13):

$$\beta_1 = 1 - \beta_2 \tag{A.14a}$$

$$\beta_3 = \beta_4 \tag{A.14b}$$

$$\beta_3 = -\beta_5/2 \tag{A.14c}$$

$$\gamma_2 = -\gamma_3 \tag{A.14d}$$

The first three constraints apply to the standard cost function, while the fourth applies only to factor bias.[36]

[35] This first-order approximation follows from how Eqs. (A.4), (A.6), and (A.7) imply

$$\frac{\partial\phi}{\partial \ln r^*} = \frac{\partial^2 \ln c^*}{\partial^2 \ln r^*} = -\frac{\partial^2 \ln c^*}{\partial \ln r^* \partial \ln v^*} = -\frac{\partial\phi}{\partial \ln v^*} = \phi(1-\phi)(1-\sigma)$$

[36] It is possible to test if the elasticity of substitution varies with Z_j by adding the term $(\hat{r}_j - \hat{v}_j)^2 Z_j\gamma_3$. However, we do not find interactions for the quadratic interaction to be significant and thus have left a heterogeneous elasticity of substitution out of the formulation.

The elasticity of housing supply is derived from Shepard's Lemma for land (A.3) by taking the differential:

$$\hat{L} + \hat{A}^L - \hat{Y} = d\ln c_r^* \tag{A.15}$$

$$= -\sigma(1-\phi)\left(\hat{r}_j - \hat{A}_j^L - \hat{v}_j + \hat{A}_j^M\right) \tag{A.16}$$

where the last line obtains from a first-order approximation. Now, from the first-order equilibrium condition for housing costs, (A.5), it follows that:

$$\hat{r}_j - \hat{v}_j = \frac{\hat{p}_j - \hat{v}_j}{\phi} + \hat{A}_j^L + \frac{1-\phi}{\phi}\hat{A}_j^M.$$

Combining the last two equations to eliminate $\hat{r}_j$ and rearranging, we are left with a general supply equation:

$$\hat{Y} = \hat{L} + \hat{A}^L + \sigma\frac{1-\phi}{\phi}\left(\hat{p}_j - \hat{v}_j + \hat{A}_j^M\right) \tag{A.17}$$

The formula in (5) comes from substituting in $\hat{A}^L = \hat{A} + (1-\phi)\hat{B}$ and $\hat{A}^M = \hat{A} - \phi\hat{B}$ and rearranging.

The derivation of the estimate of trade productivity in Eq. (7) is parallel to the first-order derivation above. The mobility condition for workers requires differentiating the log expenditure function for workers $\ln\left[e(p_j; Q_j^k, \bar{u}^k)\right] = \ln\left(w_j^k + I^k\right)$. The expression in (6) follows from:

$$\frac{\partial \ln(w+I)}{\partial \ln w} = \frac{w}{w+I} \equiv t$$

$$\frac{\partial \ln e}{\partial \ln p} = \frac{py}{e} \equiv s$$

$$\frac{\partial \ln e}{\partial \ln Q} = \frac{Q}{e}\frac{\partial e}{\partial Q} = 1$$

where the last line follows from the normalization of Q described in Section 2.2.

Appendix B. Simultaneity and omitted variable bias formulas

First consider a simplified Cobb-Douglas case without factor bias ($\sigma = 1$ and $\hat{B}_j^Y = 0$), using wages as in (8), imposing $\hat{Q}_j^X = \hat{Q}_j^Y$, and where trade productivity is orthogonal to quality of life and housing productivity. Then the expectation of the OLS estimator of ϕ in (11), ϕ^*, is:

$$E[\hat{\phi}^*] = \phi\left\{1 - s^Y\frac{s^Y var(\zeta_j) + cov(\hat{Q}_j, \zeta_j + \varepsilon_j)}{var(\hat{Q}_j + s^Y\zeta_j)}\right\}. \tag{A.18}$$

The term $s^Y var(\zeta_j)$ determines the downward simultaneity bias if not all housing productivity shifts are accounted for. High housing productivity raises land values but not housing prices, attenuating the cost-share estimate. Indeed, if variation in land prices were driven entirely by unobserved housing productivity, then $\hat{\phi}^*$ would be zero.

The term $cov(\hat{Q}_j, \zeta_j + \varepsilon_j)$ determines a standard omitted variable bias. If, as indeed we find, metro areas with high quality of life tend to have low housing productivity, this bias will be upwards. The net effects depend largely on how ζ_j varies relative to $\hat{Q}_j$. Better measures of Z should lower variation in ζ_j, reducing the bias in ϕ^*, which is properly identified from variation in $\hat{Q}_j$.

To consider the role of trade productivity, the full formula is given by:

$$E[\hat{\phi}^*] = \phi\left\{1 - \frac{cov(\hat{Q} + \hat{A}^{Y\prime}_{,}\hat{A}^{Y\prime})var(\hat{A}^{X\prime}) - cov(\hat{Q} + \hat{A}^{Y\prime}, \hat{A}^{X\prime})cov(\hat{A}^{Y\prime}, \hat{A}^{X\prime})}{var(\hat{Q} + \hat{A}^{Y\prime})var(\hat{A}^{X\prime}) - \left[cov(\hat{Q} + \hat{A}^{Y\prime}, \hat{A}_X)\right]^2}\right\} \tag{A.19}$$

where $\hat{A}^{k\prime} = s^k\hat{A}^k, k \in \{X, Y\}$.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jue.2018.06.002.

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