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David Albouy
Gabriel Ehrlich

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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. Conditioning on housing demand, OLS and IV estimates imply that stringent regulatory and geographic restrictions increase housing prices relative to input costs substantially. 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 costliest, 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.

David Albouy
Department of Economics
University of Illinois at Urbana-Champaign
214 David Kinley Hall
Urbana, IL 61801-3606
and NBER
albouy@illinois.edu

Gabriel Ehrlich
Department of Economics
University of Michigan
611 Tappan St
Ann Arbor, MI 48109-1220
gehrlich@umich.edu

1 Introduction

The price of housing varies tremendously across the United States: for instance, the price of the typical home in Flint, MI is $33 thousand, while in Malibu, CA it is well over $1.9 million.[1] While differences in demand clearly play a role in determining these prices, the inability of supply to equalize housing prices has attracted considerable attention (see, e.g., Glaeser and Gyourko, 2005, Saiz, 2010). Many commentators blame land-use restrictions for declining housing affordability, with Summers (2014) arguing 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, land-use restrictions are often locally supported and are argued to increase local housing demand by improve local quality of life and the provision of public goods (Hamilton, 1975, Brueckner, 1981, Fischel, 1987). Consequently, analyses that find land-use restrictions raise house prices could in principle reflect either increases in housing demand or reductions in housing supply. The social benefits of land-use regulation thus remain uncertain and debatable.

We help to resolve this debate, demonstrating that land-use restrictions raise house prices more by limiting supply than by increasing demand. In short, the typical land-use restriction appears to raise the cost of housing relative to land, implying that it lowers what we call "housing productivity." At the same time, it does little to raise housing prices relative to local wage levels, meaning it barely raises residents' "willingness-to-pay" for local quality-of-life amenities. Together, these findings imply that the typical land-use restriction reduces social welfare. Quantitatively, we estimate that observed land-use restrictions raise housing costs by 15 percentage points, reducing welfare on average by 2.3 percent of income.[2]

More concretely, our estimation strategy posits a cost function for housing that depends on land and construction input prices, and a multiplicative productivity factor in the spirit of Hicks (1932) and Solow (1957). Land-use restrictions and (analogously) geographic restrictions shift this "housing productivity" factor. Housing is more expensive in areas with: i) high land values; ii) high construction costs; and, iii) low housing productivity.

We embed this cost function for housing into an equilibrium system of cities. This system accounts for how fundamental determinants of supply and demand — namely, local

[1] Home values are from the 2011 to 2015 American Community Survey American Factfinder.

[2] 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 percent), and scaling the implied increase in costs by housing's share of the average expenditure bundle of 16 percent.

quality of life and productivity in both housing and traded sectors — determine the price of housing and land simultaneously (Roback, 1982, Albouy, 2016). By conditioning on land and construction prices, our strategy controls for demand-side determinants of housing prices to isolate supply-side determinants.

Using novel estimates of U.S. land values adapted from Albouy et al. (2017), we find that land-use restrictions — as measured by the Wharton Residential Land-Use Restriction Index (WRLURI) of Gyourko et al. (2008) — impose a "regulatory tax" that drives a wedge between output (housing) prices and input (land and construction) prices. Analogously, geographic restrictions as measured by Saiz (2010) also lower housing productivity. These estimates hold when we estimate housing cost function parameters using either ordinary least squares (OLS) or instrumental variable (IV) methods, as well as when we calibrate the housing cost function directly using a wide range of values. 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 WRLURI, we find state political and court involvement predict the largest increases in costs.

Our new measure of metropolitan housing productivity supplements other metropolitan indices of economic value, namely a productivity index for firms in the traded sector—as in Beeson and Eberts (1989), Gabriel and Rosenthal (2004), Shapiro (2006), and Albouy (2016)—and an index 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 percent of total housing costs. Contrary to common assumptions (e.g., Rappaport, 2008) that productivity levels in tradeables and housing are equal, we find the two are negatively correlated across metro areas. For example, while San Francisco has one of the most productive traded sectors, it has among the least productive housing sectors.

Furthermore, we consolidate the predicted efficiency loss of the WRLURI subindices into a novel "Regulatory Cost Index," or RCI. The RCI measures the extent to which observed regulations reduce housing productivity. It explains two-fifths of the variance between input costs and output prices. While the WRLURI provides a widely-used single index of the stringency of land-use regulations through factor analysis, our RCI is based on the marginal cost each regulation imposes, and has a stronger cardinal interpretation. We find costs measured by the RCI rise along with city population and density.

Besides estimating housing productivity, the cross-metropolitan variation in input prices and restriction measures provide novel estimates of a cost function for all housing. With only four variables, the model explains 86 percent of housing-price variation across metros. The housing-to-land price gradient implies that land typically accounts for one-third of housing costs, which rises from 6 to 50 percent from low to high-value metros, consistent with an elasticity of substitution between inputs below one.

Our analysis concludes by considering whether the quality-of-life benefits of land-use restrictions come with benefits that offset their costs. To do this, we estimate how households' willingness to pay to live in a metro area changes with regulations: an increasing relationship would suggest that regulations raise households' quality of life. Households do pay more to be in areas that are highly regulated, but this relationship disappears after controlling for amenities such as climate and geography. Similarly, we do not find that regulations raise the value of local land. Taken together, our results suggest that typical land regulations impose costs that exceed their benefits.

2 Literature on Housing Production and Land Values

While there are many estimates of housing production parameters, there are no comparable measures of housing productivity or the RCI. The cost effects of land-use restrictions are identified from the wedge between housing prices and input costs, largely shielding them from the critique that these restrictions are positively correlated with demand factors, made here and by Davidoff et al. (2016).

That said, there is also novelty to our estimation of the housing cost function using metro-level variation in transaction-based land prices, construction input prices, and restrictions. Economists since Ricardo (1817) and George (1884) have sought to quantify the share of property values attributable to land. In fact, Ricardo's famous "Law of Rent" predicts that the cost share of land should approach zero in the lowest value areas. McDonald (1981) surveys more modern predecessors — including Rosen (1978), Polinsky and Ellwood (1979), Arnott and Lewis (1979) — and finds most estimates of the elasticity of substitution (ES) between land and other inputs to be loosely centered around 0.5, pointing out that measurement error may bias these estimates downwards.[3]

Thorsnes (1997) is unique among our predecessors in using market transactions for land, with 219 lots from Portland. His data imply land's cost share is 0.22, while his estimates of the ES center around 0.9 [4] Epple et al. (2010) use an estimator based on

[3]Our approach, focused on prices pooled at the city level, should be less susceptible to measurement error.

[4]Thorsnes (1997) and Sirmans et al. (1979) estimate a variable ES using small samples drawn from a

how assessed land values per square foot vary with property values per square foot. They estimate a cost share of land of 0.14 in Pittsburgh and 0.21 in Raleigh, each with an ES close to one. Combes et al. (2017) use a method comparing construction costs to land. They find land's share is near 0.3 for Paris and large agglomerations, and near 0.2 for the rest of France, with an ES close to 0.9. These studies do not exploit variation in regulation, geography or construction prices, and focus on new buildings, while our measure is for the entire housing stock.

Studies that find an ES of one — i.e., that the production function is of a Cobb-Douglas form — do not sit well with studies that find cost shares that vary across cities, or with Ricardo's Law of Rent. With an ES of one, cost shares should be constant with a stable technology. A similar tension exists with studies that find that housing supply is often more inelastic in expensive cities, e.g. Green et al. (2005), Saiz (2010). When land supply is fixed, a standard (partial-equilibrium) own-price elasticity of housing supply in a city j is

$$\eta_j^Y = \sigma^Y \frac{1 - \phi_j^L}{\phi_j^L} \tag{1}$$

where σ^Y is the ES, and ϕ_j^L is the local cost share of land. If $\sigma^Y = 1$ and ϕ_j^L does not change, neither should η_j^Y. Explaining variation in housing supply elasticities requires either a theory of varying technology or of varying land supply, neither of which is well developed. On the other hand, an ES of less than one allows land prices to reduce the price elasticity of housing supply.[5]

A few studies have examined more limited land and housing value data using less formal methods. Rose (1992) examines 27 cities in Japan and finds that geographic restrictions raise land and housing values. Davis and Palumbo (2008) use time series methods to estimate that the cost share of land in a sample of large U.S. metropolitan areas rose considerably from 1984 to 2004. Ihlanfeldt (2007) takes assessed land values from tax rolls in 25 Florida counties, and finds that land-use regulations predict higher housing prices but lower land values in a reduced-form framework. Glaeser and Gyourko (2003) and Glaeser and Gyourko (2005) use an enhanced residual method to infer land values, and in a sample of 20 cities — in a model without substitution between land and non-land inputs — find

handful of cities. Sirmans et al. reject the hypothesis of a constant ES, but Thorsnes finds that, "... the CES is the appropriate functional form."

[5] Saiz (2010) assumes $\sigma^Y = 0$, but allows for heterogeneous land supply in a mono-centric city, with differences in an arc of expansion explaining city-specific elasticities. Albouy and Stuart (2014) consider both the intensive (land fixed) and extensive (land variable) margins of housing supply, and find evidence of heterogeneity along both margins.

that housing and land values differ most in cities where rezoning requests take the longest.[6] They also find that the price of units in Manhattan multi-story buildings far exceeds the marginal cost of producing them, attributing the difference to regulation. They argue regulatory costs exceed their benefits, assessed mainly from the value of preserving views.

Unlike these studies, our approach (i) applies nationwide, (ii) examines the precise costs of land-use restrictions, and (iii) offers tests of the validity of our specification. Waights (2015) builds on our approach using panel data and finds similar results for England, including an ES less than one and a negative welfare consequence of land-use restrictions.

3 Model of Land Values and Housing Production

Our econometric model estimates a cost function embedded within a general-equilibrium model of urban areas, similar to Roback (1982). Albouy (2016) develops predictions on how local productivity should affect housing and land values differently, but lacks the data to test them.[7] The national economy contains many cities indexed by j, which produce a numeraire good, X, traded across cities, and housing, Y, which is not traded across cities, and has a local price, p_j.

3.1 Cost Function for Housing with Productivity Shifts

Cities differ in their productivity in their total productivity in the housing sector, A_j^Y. Firms produce housing, Y_j, with land, L, and "structural" inputs (for installation and materials), M. This latter measure includes local labor, and all other time and capital costs of building.[8]

[6] Their estimated zoning tax is zero in half of those cities. Nonetheless, they find that "...a 1-unit increase in the categorical zoning lag variable is associated with a 15-percentage-point increase in the amount of the regulatory tax. While this sample size is quite small and no causality can be inferred, it still is comforting that the places we estimate to have regulatory tax levels that are high are in fact those with more onerous zoning."

[7] Roback (1982) first proposed a model that considers housing separately from land, but did not develop or test it empirically. She does say on pages 1265-6: "if [an amenity] s inhibits the production of nontraded goods, this simply has the direct effect of raising costs. For example, houses are probably more expensive to build in a swamp." This is consistent with the theory we develop.

[8] While it is easy to interpret the production model as applying to new housing construction, it is meant to apply generally to all housing. The income that accrues to residential land and the residential construction sector appears to be too small to account for the income spent on housing. We must also include maintenance costs, as well as labor and capital costs (including time) associated with getting new buildings approved. Over time, structures tend to depreciate, making land relatively more valuable than in new construction. At the same time, new construction typically involves legal, entrepreneurial, and various time and bureaucratic costs. These inputs are generally labor intensive, and thus we proxy them with "structural" inputs. The estimated cost shares should reflect these additional inputs as well as structural depreciation.

This obeys the relationship

$$Y = A_j^Y F^Y(L, M; B_j^Y) \tag{2}$$

where F_j^Y is concave and exhibits constant returns to scale (CRS) at the firm level. Housing productivity, A_j^Y, is a city-level characteristic that may be determined endogenously by city characteristics such as population size. The term B_j^Y captures the relative productivity of land to structural inputs, or factor bias, in city j. In our primary model we ignore variation in B_j, but include it in an extended model. Greater details are provided in Appendix A.

Assume that input and output markets are perfectly competitive. Land earns a city-specific price, r_j, while structural inputs cost v_j per unit.[9] By CRS, marginal and average costs are equal, and given by the unit cost function $c^Y(r_j, v_j; B_j^Y)/A_j^Y \equiv \min_{L,M}\{r_j L + v_j M : A_j^Y F^Y(L, M; B_j^Y) = 1\}$. The equilibrium condition for housing output is that in every city j (with positive production) housing prices should equal unit costs:[10]

$$p_j = c^Y(r_j, v_j; B_j^Y)/A_j^Y. \tag{3}$$

Figure 1a illustrates how we estimate housing productivity, A_j^Y. The thick solid curve represents the cost function for cities with average productivity, holding v_j constant. As land values rise from Denver to New York, housing prices rise, albeit at a diminishing rate, as housing producers substitute away from land as a factor. The higher, thinner curve represents costs for a city with lower productivity, such as San Francisco. San Francisco's high price relative to New York, despite its identical factor costs, reveal its lower productivity.

Figure 1b shows how the curves in 1a changes when prices are transformed by loga-

[9]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.

[10]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 did not change our other results substantially. As for input markets, numerous empirical studies support the hypothesis that the construction sector is competitive. Considering evidence from the 1997 Economic Census, 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 (average cost divided by marginal cost) as 1.00, 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.

rithms. Using hat notation, $\hat{z}^j$ represents, for any variable z, city j's log deviation from the national average, $\bar{z}$, i.e. $\hat{z}^j = \ln z^j - \ln \overline{z}$. A first-order log-linear approximation of (3) expresses how housing prices vary with input prices and productivity: $\hat{p}_j = \phi^L \hat{r}_j + (1-\phi^L)\hat{v}_j - \hat{A}^Y_j$. ϕ^L is the cost share of land at the average. A^Y_j is normalized so that a one-point increase in $\hat{A}^Y_j$ corresponds to a one-point reduction in log costs.[11]

A second-order approximation of (3) reveals two more parameters: the ES, σ^Y, and differences in factor bias, B_j:

$$\hat{p}_j = \phi^L \hat{r}_j + (1-\phi^L)\hat{v}_j + \frac{1}{2}\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{v}_j - \hat{B}^Y_j)^2 - \hat{A}^Y_j, \tag{4}$$

The data will support $\sigma^Y < 1$ if output prices increase in the square of the factor-price differences, $(\hat{r}_j - \hat{v}_j)^2$. Factor biases against land, $-\hat{B}_j$, have a similar quadratic effect.

The third term accounts for changing cost shares of land. The cost-share in city j, ϕ^L_j, differs from the national average by

$$\phi^L_j - \phi^L = \phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{v}_j - \hat{B}^Y_j) \tag{5}$$

When $\sigma^Y < 1$, this share rises with the relative price of land r_j/v_j, and falls with land's factor bias, B_j. A rising cost share then puts greater weight on land's price in determining costs, as seen in the quadratic term in (4). The cost share formula also predicts that the partial-equilibrium supply elasticity in (1) is lower in places with high land prices or where productivity is biased against land. When $\sigma^Y = 1$, the Cobb-Douglas case, differences in price elasticity must instead be related to changes in parameter values or in land supply elasticities.

The estimates of $\hat{A}^Y_j$ assume that a single ES describes production in all cities. If this elasticity varies, the estimates will conflate a lower elasticity with lower productivity. Figures 1a and 1b illustrate this possibility by comparing the case of $\sigma^Y = 1$, in solid curves, with $\sigma^Y < 1$, in dashed curves. With lower substitutability, the cost function is less curved, as producers are less able to substitute away from land in higher-value cities. Thus low productivity and low substitutability will both tend to raise housing costs, despite their conceptually distinct impacts on the shape of the housing production function.[12]

[11]Bias is formally, the productivity of land relative to structural inputs, $B_j \equiv A^{YL}_j / A^{YM}_j$, where A^{Yk}_j is the productivity of each factor k. Formal derivations in Appendix A show that we can write $\hat{A}^Y_j = \phi^N \hat{A}^{YL}_j + (1-\phi^N)\hat{A}^{YM}_j$ and $\hat{B}^Y_j = \hat{A}^{YL} - \hat{A}^{YM}$.

[12]We keep σ^Y_j fixed in the analysis because we did not find any evidence of heterogeneity when we exam-

3.2 Adapting and Testing the Translog Cost Function

Because it is impossible to observe housing productivity directly, it must be inferred indirectly. To clarify the measurement, assume housing productivity and factor bias are determined in part by a vector of observable restrictions, Z, which is partitioned into regulatory and geographic components $Z = [Z^R, Z^G]$. In addition, they are determined by unobserved city-specific components, $\xi_j = [\xi_{Aj}, \xi_{Bj}]$, such that

$$\hat{A}_j^Y = -Z_j\delta_A - \xi_{Aj} \tag{6a}$$

$$\hat{B}_j^Y = -Z_j\delta_B - \xi_{Bj} \tag{6b}$$

A positive δ_A therefore indicates that a restriction *reduces* productivity; a positive δ_B indicates that a restriction is biased *against* land.

Substituting in equations (6a) and (6b) into (4), it is possible to write out the a reduced-form equation that contains all of the structural restrictions:

$$\hat{p}_j - \hat{v}_j = \beta_1(\hat{r}_j - \hat{v}_j) + \beta_3(\hat{r}_j - \hat{v}_j)^2 + \gamma_1 Z_j + \gamma_2 Z_j(\hat{r}_j - \hat{v}_j)_j + \zeta_j + \varepsilon_j. \tag{7}$$

The reduced-form coefficients correspond to the following structural parameters:

$$\beta_1 = \phi^L \tag{8a}$$

$$\beta_3 = (1/2)\phi^L(1-\phi^L)(1-\sigma^Y) \tag{8b}$$

$$\gamma_1 = \delta_A \tag{8c}$$

$$\gamma_2 = \phi^L(1-\phi^L)(1-\sigma^Y)\delta_B = 2\beta_3\delta_B \tag{8d}$$

Inverting these equations, the housing cost parameters are given by $\phi^L = \beta_1$, $\sigma^Y = 1 - 2\beta_3/[\beta_1(1-\beta_1)]$, $\delta_A = \gamma_1$, and $\delta_B = \gamma_2/(2\beta_3)$. Thus, β_1 identifies the distribution parameter, ϕ^L, and together with β_3 it identifies the substitution parameter σ^Y. 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 $\gamma_2\beta_3 > 0$.

The error term in (7) consist of two components. The ζ_j component consists mainly of unobserved determinants of productivity and bias, and is equal to ξ_{Aj} when $\hat{B}_j = 0$. The ε_j component captures any sampling, measurement or specification errors. The latter could result from market power in the housing sector, or disequilibrium forces causing prices to

ined the data.

deviate from costs. It is important to consider these possibilities, as the estimated residuals in the model may or may not be caused by unobserved differences in productivity.

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

$$\hat{p}_j = \beta_1 \hat{r}_j + \beta_2 \hat{v}_j + \beta_3 (\hat{r}_j)^2 + \beta_4 (\hat{v}_j)^2 + \beta_5 (\hat{r}_j \hat{v}_j) + \gamma_1 Z_j + \gamma_2 Z_j \hat{r}_j + \gamma_3 Z_j \hat{v}_j + \varepsilon'_j \quad (9)$$

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

$$\beta_1 = 1 - \beta_2 \quad (10a)$$

$$\beta_3 = \beta_4 = -\beta_5/2 \quad (10b)$$

While our 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 or diseconomies, will be reflected in A_Y^j, as suggested by the evidence in section 6.2 below.[13] The extended model, with $\delta_B \neq 0$ also imposed the restriction that $\gamma_2 = -\gamma_3$.

The econometric model allows us to test for the popular Cobb-Douglas (CD) technology, which imposes the restriction $\sigma^Y = 1$ in (4) or

$$\beta_3 = \beta_4 = \beta_5 = 0. \quad (11)$$

in (9). To simplify exposition, we impose (11) in the following subsection.

3.3 Simultaneous Determination of Housing and Land Prices

It is important to consider that housing, land, and construction prices are determined simultaneously. To do this, consider the equilibrium of a system of cities adapted from Roback (1982) and Albouy (2016). There are two sectors in the economy, producing a traded good

[13]Convexity of the cost gradient is limited by $\sigma^Y \geq 0$, which implies $\beta_3 \leq 0.5\beta_1(1-\beta_1)$. Finding this inequality holds is an auxiliary test of the model. Note, the second-order approximation of the cost function (i.e. the translog) is not a constant-elasticity form. Hence, the ES we estimate is evaluated at the sample mean parameter values (see Griliches and Ringstad, 1971). To our knowledge, ours is the first empirical study to identify this housing elasticity from an explicit quadratic form and to test a translog cost function using such a wide spatial cross-section of input and output prices for housing or any other good.

x and a non-traded (housing) good, y. Land and structural costs are determined simultaneously with housing prices from differences in housing productivity, A_j^Y, trade productivity, A_j^X, and quality of life, Q_j. To simplify, assume away federal taxes and land in the traded sector. 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 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.

As a baseline, consider the case where 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. As shown in appendix A, this mobility condition implies

$$\hat{Q}_j^k = s^Y \hat{p}_j - s^w \hat{w}_j^k,\ k = X, Y, \tag{12}$$

i.e., higher quality of life must offset high prices or low after-tax wages. Q_j^k is normalized such that $\hat{Q}_j^k$ of 0.01 is equivalent in utility to a one-percent rise in total consumption. s^Y is the expenditure share on housing and s^w is labor's share of income (assumed equal across sectors). The aggregate quality of life differential 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. $\hat{w} \equiv \lambda \hat{w}_j^X + (1 - \lambda)\hat{w}_j^Y$.

Traded output has a uniform price of one across all cities. It is produced with CRS and CD technology, with A_j^X being factor neutral. Because the output price is uniform, the trade-productivity differential is proportional to wages:

$$\hat{A}_j^X = \theta^N \hat{w}_j^X, \tag{13}$$

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

Structural inputs are produced with local labor and traded capital according to production function $M_j = (N^Y)^a (K^Y)^{1-a}$. This implies $\hat{v}_j = a\hat{w}_j^Y$, where a is the cost-share of labor in structural inputs. Defining $\phi^N = a(1 - \phi^L)$, recasts an alternative measure of housing productivity on the same principle of input vs output costs, but using wages:

$$\hat{A}_j^Y = \phi^L \hat{r}_j + \phi^N \hat{w}_j^Y - \hat{p}_j. \tag{14}$$

The sum of productivity levels in both sectors, the total-productivity differential of a city, is $\hat{A}_j^{TOT} \equiv s^X \hat{A}_j^X + s^Y \hat{A}_j^Y$, where $s^X = 1 - s^Y$.

A recursive set of solutions is obtained by combining the equations (12), (13), and (14):

$$s^w \hat{w}_j^X = \lambda^{-1} s^X \hat{A}_j^X \tag{15a}$$
$$s^Y \hat{p}_j = \hat{Q}_j^X + \lambda^{-1} s^X \hat{A}_j^X \tag{15b}$$
$$s^w \hat{w}_j^Y = \hat{Q}_j^X - \hat{Q}_j^Y + \lambda^{-1} s^X \hat{A}_j^X \tag{15c}$$
$$s^R \hat{r}_j = \lambda \hat{Q}_j^X + (1-\lambda)\hat{Q}_j^Y + s^X \hat{A}_j^X + s^Y \hat{A}_j^Y = \hat{Q}_j + \hat{A}_j^{TOT} \tag{15d}$$

where $s^R = s^Y \phi^L$ 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 include housing productivity and quality of life for housing workers.

Improvements in local housing productivity do not reduce the unconditional price of housing, a point elaborated on by Aura and Davidoff (2008). In this model, they instead raise land values. 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.

In the case of preference heterogeneity, the willingness-to-pay of residents captured by Q_j can be decomposed into two elements: a fundamental component, Q_{0j}, reflecting the typical value of amenities, and an idiosyncratic component, ω_{ij}, reflecting heterogeneous tastes. With positive assortative matching to cities, the marginal and average value of ω_{ij} will be higher when the population is low than when it is high, as households that value the city most bid up housing prices, outbidding those who value the city less. Because low housing productivity will reduce the population, the marginal resident will have a higher willingness-to-pay than if the population were larger. With higher housing productivity, the population expands, and the willingness to pay of the marginal resident, $\hat{Q}_j = \hat{Q}_{0j} + \omega_{ij}$ falls through ω_{ij}. This causes prices to fall, through equation (15b). Ceteris paribus, this should cause $\hat{Q}_j$ and $\hat{A}_j^Y$ to be negatively correlated even if policies that improve $\hat{A}_j^Y$ have no effects on the fundamental amenities in $\hat{Q}_{0j}$. We revisit this point in the context of land supply in subsection 6.3.

The mathematics in these two richer cases are complicated, but are described and simulated in Albouy and Farahani (2017) when $\hat{Q}_j^X = \hat{Q}_j^Y$. The analysis suggests that land is too minor in the non-traded sector for wages to respond much to housing productivity. Preference heterogeneity reduces how much land values rise with housing productivity, since their derived demand through housing prices grows weaker. Regardless, the wedge between output and input prices described in (4) remains unchanged by these demand-related considerations. In fact, the frictions introduced by heterogeneity mitigate the potential problems of simultaneity in estimating the model described in section 3.4.

3.4 Identification, Simultaneity, and Instrumental Variables

The econometric specification in equation (9) regresses housing costs $\hat{p}_j$ on land values $\hat{r}_j$, structural prices $\hat{v}_j$, and restrictions, $\hat{Z}_j$. The primary model without factor bias ($\hat{B}_j^Y = 0$) implies the residual is either unobserved housing productivity, ζ_j, or a more general error term, ε_j. This approach 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 together.

Identifying housing productivity and how it is affected by restrictions does require accurate values of the housing cost parameters. OLS estimates of these parameters are consistent if $\zeta_j = 0$, ε_j is orthogonal to the regressors, and price variation is driven by quality of life and trade productivity (wages).

To see this, consider a simplified CD case without factor bias ($\sigma^Y = 1$ and $\hat{B}_j^Y = 0$), using wages as in (14), imposing $\hat{Q}_j^X = \hat{Q}_j^Y$, and where trade-productivity is orthogonal to quality of life and housing productivity. Then the OLS estimator of ϕ^L in (7), ϕ^{L*}, is

$$E[\hat{\phi^{L*}}] = \phi^L \left\{ 1 - s^Y \frac{s^Y var(\zeta_j) + cov(\hat{Q}_j, \zeta_j + \varepsilon_j)}{var(\hat{Q}_j + s^Y \zeta_j)} \right\} \tag{16}$$

The first term, with $var(\zeta_j)$ reflects a downward simultaneity bias: in equations (15b) and (15d) high housing productivity raises land values without raising housing prices. If variation in land prices is driven entirely by unobserved housing productivity, then $\hat{\phi^{L*}}$ would be zero. The second term, $cov(\hat{Q}_j, \zeta_j + \varepsilon_j)$ reflects a standard omitted variable bias. Because we find later that high quality-of-life places tend to have low housing productivity, in practice this bias will be upwards. The net effects depend largely on how ζ_j varies relative to $\hat{Q}_j$. More extensive measures in Z should lower variation in ζ_j, removing bias from the OLS estimator of ϕ_L as it is identified off of variation in $\hat{Q}_j$.[14]

A solution to these potential problems is to find instrumental variables (IVs) for land values, as well as structural input prices. Variables that influence quality of life Q^j or trade productivity A^X_j affect land and housing values in tandem. These variables need to be unrelated to unobserved housing productivity ζ_j. Motivated by the theory, we consider two instruments. The first is the inverse of the distance to the nearest saltwater coast, a predictor of Q^j and 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 Q^j.[15]

An additional concern regarding identification in the econometric model is that regulatory restrictions may be endogenously determined and 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 argues that the nontraditional, and especially Evangelical, Christians measured by the first instrument have an "ethics and philosophy ... deeply rooted in individualism and the advocacy of limited government role" (p. 1276) that is associated with a less stringent regime of land use regulations. Saiz also argues that a higher share of expenditures related to protective inspections is indicative of a general tendency for government to regulate economic activity, which extends to residential land use. Saiz's model requires that the instruments be uncorrelated with both unobserved demand and supply factors; our cost model is less stringent in requiring that the instruments be uncorrelated with unobserved supply factors alone.

[14]To consider the role of trade productivity, the full formula is given by

$$E[\phi^{\hat{L}*}] = \phi^L \left\{ 1 - \frac{cov(\hat{Q} + \hat{A}^{Y\prime}_{,} \hat{A}^{Y\prime}) var(\hat{A}^{X\prime}) - cov(\hat{Q} + \hat{A}^{Y\prime}, \hat{A}^{X\prime}) cov(\hat{A}^{Y\prime}, \hat{A}^{X\prime})}{var(\hat{Q} + \hat{A}^{Y\prime}) var(\hat{A}^{X\prime}) - \left[cov(\hat{Q} + \hat{A}^{Y\prime}, \hat{A}_X) \right]^2} \right\} \quad (17)$$

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

[15]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 MSA level.

4 Data and Metropolitan Indicators

The residential land-value index used to estimate the housing cost function is adapted from Albouy et al. (2017), who describe it in far greater detail. It is based on market transactions from the CoStar group, and uses a regression framework which controls for parcel acreage and intended use. It applies a novel 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. (2017) 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 plots, 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 Prices

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). Prior to 2005, the ACS is too coarse geographically; our land transaction data end in 2010. As described fully in Appendix B, 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-MSA interaction, ψ_{ijt}, in the equation $\ln p_{ijt} = \mathbf{X}_{ijt} + \psi_{ijt} + e_{ijt}$. The indicator variables ψ_{ijt} provide the metro-level indices, denoted $\hat{p}$.[16] We aggregate the inter-metropolitan index of housing prices, $\hat{p}_{jt}$, normalized to have mean zero, across years for display.

Metropolitan wage differentials 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 figure A shows that $\hat{w}_j^Y$ is similar to, but more dispersed than, overall wages, $\hat{w}_j$. We use the construction-wage index as an alternative proxy for the price of structural inputs. Appendix figure B shows how the two are highly correlated.[17]

Our main price index for structural inputs, v_j, comes from the Building Construction Cost data from the RS Means company. This index covers the costs of installation and

[16] Alternative methods using-price differences, such as letting the coefficient β vary across cities, produces similar indicators (Albouy et al., 2016).

[17] Somerville (1999) critiques the RS Means index for using union wages, which account for 35 percent of these costs. However, our analysis using construction wages yield similar results.

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 an MSA contains multiple 3-digit zipcodes, we weight each by the share of the MSA's housing units in each zipcode.

The housing-price, land-value, construction cost, and construction-wage indices are reported in columns 2 through 5 of table 1. They tend to be positively correlated with each other and metro population, reported in column 1, highlighting the importance of including measures of both land and structural input costs. We mark metros in the lowest decile of population growth between 1980 and 2010 with a "*" in case the equilibrium condition (3) does not apply well to these areas.

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. These responses form the basis of 11 subindices, coded so that higher scores correspond to greater regulatory stringency.[18] The base data for the WRLURI is for the municipal level; we calculate the WRLURI and subindices at the MSA level by weighting the individual municipal values using sampling weights provided by the authors, multiplied by each municipality's population proportion within its MSA. The authors construct a single aggregate WRLURI index through factor analysis: we consider both their aggregate index and the subindices in our analysis. 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 WRLURI 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 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 degrees or steeper. We consider both Saiz's aggregate index and his separate indices based on solid and flat land, each of which is renormalized as a $z-$score.

[18]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).

5 Cost-Function Estimates

The indices from section 4 provide considerable variation to test and estimate the cost function presented in section 3, and to examine how costs are influenced by geography and regulation. We restrict our analysis to MSAs with at least 10 land-sale observations, and years with at least 5. For our main estimates, the MSAs must also have available WRLURI, Saiz and construction-price indices, leaving 230 MSAs and 1,103 MSA-years. Regressions are weighted by the number of housing units in each MSA.

5.1 Base OLS Estimates and Tests of the Housing Cost Model

Figure 2 plots metropolitan housing prices against land values. The simple regression line's slope of 0.52 corresponds to the cost share of land, ϕ_L, assuming CD production and no other input cost or productivity differences. The convex gradient in the quadratic regression implies that the average cost-share of land increases with land values, yielding an imprecise estimate of the ES of 0.47. The vertical distance between each MSA marker and the estimated regression line forms the basis of our estimate of housing productivity. Taken at face value, San Francisco has low housing productivity and Las Vegas has high housing productivity.

The next step of the analysis is to add in construction prices. These are plotted against land values in figure 3. The two are strongly correlated, but the scale of the horizontal axis for land-value differentials is much larger than the scale on the vertical than construction prices. Most of the variation in relative factor prices $\hat{r}_j - \hat{v}_j$, used to identify the housing cost parameters, is driven by land prices. These data are used to estimate the cost surface shown in figure 4, omitting variation in Z. As before, cities with housing prices above this surface are inferred to have lower housing productivity. Figure 3 plots estimated input cost level curves for the surface in 4. From equation (4), these curves that satisfy $\phi^L \hat{r}_j + \phi^M \hat{v}_j + \phi^L \phi^M (1 - \sigma^Y)(\hat{r}_j - \hat{v}_j)^2 = c$ for a constant c. Since $c = \hat{p}_j + \hat{A}_j^Y$, 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. With the log-linearization, the slope of the level curve equals minus the ratio of the land cost share to the structural share, $-\phi_j^L / \phi_j^M$. Since the estimated $\sigma^Y < 1$, the curves are concave as land's cost-share increases with land's value.

Moving from these illustrations to our core model, table 2 presents cost-function estimates with the aggregate geographic and regulatory indices. Columns 1 through 3 impose

CD production, as in (11); columns 1 and 2 also impose the homogeneity constraint in (10a). 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 percent from 53 percent in figure 2 from a reduction in omitted variable bias. When the two restriction measures are included in column 2, the land share falls to 36 percent from a further reduction. As predicted, 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. The same is true of the CD constraint from (11) in column 2. Column 3 relaxes homogeneity in (10a); 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 formulation (9) that allows the ES to be non-unitary. This specification does better as the homogeneity constraints in (10a) and (10b), pass at the 5% confidence level in columns 4 or 5. The estimated ES in columns 4 and 5 are both below one-half. The large effects of the regulatory and geographic restrictions persist in these specifications.

Column 7 uses construction wages instead of the RS means index; it otherwise parallels column 5. The results are similar, although the homogeneity restriction is rejected. While this illustrates that our results are largely robust to the construction-price measure, they also suggest that the RS Means index is a more appropriate price measure. Conceptually, this is likely because it incorporates the price of non-labor inputs (i.e., materials), rather than the price of labor only.[19]

Finally, the results in column 8 present estimates from our extended model, which examines whether the regulatory or geographic restrictions are factor-biased against or towards land. This allows γ_2 to be non-zero in equation (7) by interacting the differential $\hat{r} - \hat{v}$ with the restrictions Z_j. The estimate of $\gamma_2 = 0.057 > 0$ for the regulatory interaction supports the hypothesis that land-use regulations are indeed biased against land. It implies a one standard deviation increase in regulation raises the cost share of land by 5.7 percentage points. Using this and the estimate of $\beta_2 = 0.044$, equation (8d) implies $\delta_B = 0.65$,

[19]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 equation (14). Nevertheless, The CD formulation produced a very similar estimate of $\phi^L = 0.35$ and an estimate for labor of $\phi^N = 0.39$. Interestingly, if we regress the construction wage measure on the RS means measure, we get an implied value of $a = 0.58$, which implies a similar value for ϕ^N.

meaning a one standard deviation increase reduces the relative productivity of land by almost 50 percent. While this large estimate is suggestive, the specification does not pass the additional test imposed on the reduced form equation (9) that the interaction on land prices should be equal and opposite the interaction on construction prices, i.e., $\gamma_2 = -\gamma_3$: this hypothesis is rejected at even a 1% size. As a result, we focus on the primary factor-neutral case with $\hat{B}_j = 0$.

5.2 Estimate Stability

Several exercises, reported in table 3, help gauge the stability and robustness of our estimates. All specifications in table 3 use the primary constrained model from (7), $\hat{p}_j - \hat{v}_j = \beta_1(\hat{r}_j - \hat{v}_j) + \beta_3(\hat{r}_j - \hat{v}_j)^2 + Z^j\gamma_1 + \varepsilon_j$ from column 5 of table 2, which is reproduced in column 1 of table 3 for convenience.

Columns 2 and 3 use two alternative — and less appropriate — 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 2 results in a smaller land share as well as a higher ES. Appendix figure C shows that land values for all uses vary considerably more than values for residential uses only. Thus, using an index that includes non-residential uses biases the slope and curvature of the housing cost function downwards. The results in column 4 finds that weighting all land equally, ignoring where homes are located, produces similar biases.

Column 4 considers an alternative — and also less appropriate — housing-price index, which makes no hedonic correction for housing characteristics. The results are largely similar, as differences in observed housing quality do little to affect the results except introduce more noise (as seen in the lower R-squared). If unobserved differences in housing quality resemble observed differences, these results suggest that the former should not overturn our main conclusions.

In columns 5 and 6, 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 does show stronger effects from the restrictions, providing suggestive evidence in support of the model as the restrictions should be more binding when housing demand is stronger.[20]

[20] 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).

Overall, the estimates in table 2 and columns 5 and 6 of table 3 support our key hypotheses: regulatory and geographic restrictions raise housing costs, somewhere in the range 0.07 to 0.10 for a standard deviation increase of either measure. The translog model also passes rather stringent tests of homogeneity in (10a) and (10b) despite the disparate sources of data that it uses. The housing parameters it estimates are quite plausible, with a typical cost-share of land from 0.32-0.36. The estimated ES is less stable, in the range of 0.3 to 0.6, lightly rejecting the CD hypothesis in (11).

5.3 Instrumental Variables Estimates

To assess the potential concerns regarding the endogeneity of land values and land-use regulations discussed in section 3.4, table 4 presents IV estimates of the base CD and translog specifications in table 2. Appendix tables A1 and A2 present corresponding first-stage estimates. Columns 1 and 2 present IV versions of the CD estimates in column 2 of table 2.[21] Column 1 uses inverse distance from the sea and the USDA amenity score as instruments for the differential $(\hat{r} - \hat{v})$. Column 2 adds the nontraditional Christian share and protective inspections share suggested by Saiz as instruments, and treats both the land-value differential and the regulatory index 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 the land-value differential and the regulatory index, 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 OLS estimates in column 5 of table 2. Column 3 treats only land values as potentially endogenous, using the levels and squares of the USDA amenities score and inverse distance to the sea, as well as their interaction, as instruments for the differentials $(\hat{r} - \hat{v})$ and $(\hat{r} - \hat{v})^2$. Column 4 additionally treats the regulatory index as potentially endogenous, using the nontraditional Christian share and protective inspections share, and their interactions with the first two instruments as excluded instruments. The estimated cost shares of land are again somewhat higher than in the OLS estimates in table 2, but are also less precise. The IV estimates of efficiency cost of regulations in column 4 are 14 log points per standard deviation, larger than in the OLS

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

but smaller than in the IV CD case. Column 5 uses a more limited set of instruments, using squares and interactions of the predicted land-value minus construction cost differential and regulatory restriction index from the first-stage regressions. The estimated cost share of land is similar to the OLS estimates, while the efficiency cost of regulations is higher. Tables A2 and A3 display all first-stage regressions.

In column 6 we push the IV strategy to further 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).[22] The results are qualitatively similar to those in column 8 of Table 2, suggesting that regulatory restrictions are biased against land. However, the estimated magnitude of the bias, as well as the land share and ES, are even higher than in the OLS specification.

Overall, the IV estimates are largely consistent with our OLS estimates. They suggest a somewhat higher cost share of land and larger impacts of regulatory restrictions, while being less precise. The two bottom rows of table 5 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 in the table 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.

As we emphasized earlier, the OLS estimates are not invalidated by omitted demand factors, as only supply factors should impact the cost equation. This makes the IV strategy less critical to establishing our results. Given some of the problems with the diagnostic tests, the larger standard errors, and the quality of the instruments, it is not clear that the IV estimates are preferable to the OLS estimates.[23]

5.4 Calibrating Alternative Cost Parameters

The literature on the housing cost function has offered a range of values for land's share and the ES that are not always consistent with ours. We believe that our estimation strategy, which is based on market-inferred land values across metro areas, innovates in some ways on the previous literature. Nonetheless, it is entirely possible that our estimates of the

[22] 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.

[23]

housing cost function parameters are incorrect. Because our main focus here is on housing productivity and the costs imposed by land-use regulations, we also attempt to estimate δ_A by imposing many different combinations of the cost parameters. This involves setting values of ϕ^L and σ^Y and estimating

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

Figure 5 shows the estimated effects using a range of ϕ^L from 0 to 0.5 and σ_Y from 0 to 1.2, values that span the vast majority of previous literature. The estimated effects of the restrictions decline as the cost share of land rises, and the effect of geographic restrictions rises slightly with the ES. 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 the highest levels of the cost share. These results suggest that our key finding that regulatory and geographic restrictions reduce housing productivity is not sensitive to the exact shape of the housing cost function.[24]

5.5 Disaggregate Indices and the Regulatory Cost Index

Given our finding that land-use restrictions raise housing costs, the next issue is to determine what kinds of land-use restrictions do so the most. As discussed previously, the WRLURI aggregates 11 subindices, while the Saiz index aggregates two. Column 1 of table 5 reports the factor loading of each of the WRLURI subindices in the aggregate index, ordered according to its factor load. Alongside, in column 2, are coefficient estimates from a regression of the aggregate WRLURI $z-$score on the $z-$scores for the subindices. These coefficients differ from the factor loads because of differences in samples and weights. Column 3 presents similar estimates for the Saiz subindices; the coefficients on these measures are negative because the subindices indicate land that may be available for development.

The specification in column 4 is identical to the specification in column 5 of table 2, but with the disaggregated regulatory and geographic subindices. The fit of the model is quite high, with a coefficient of variation (R^2) near 90 percent. The estimated typical cost share of land of $\phi^L = 0.332$ and ES of $\sigma^Y = 0.51$ are close to our estimates in column 5 from table 2. This small change suggests that the biases from unobserved housing-productivity determinants ζ_j discussed in subsection 3.4 are likely to be a minor as measures in Z_j seem

[24]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.

to be absorbing much of the variation.

The results for the subindices indicate that one-standard deviation increases in state political and state court involvement reduce metro-level productivity by 6 and 4 percent. Local supply restrictions raise costs by 1.5 percent. All of these estimates are significant at the 5% level. At a lower level of significance of 10%, local political pressure raises costs by 2.4%. At a significance level of 20%, approval delay, local project approval, and local assembly also all seem to play a role in raising housing costs, the latter evoking recent work by Brooks and Byron (2016). The one marginally significant negative coefficient is on exactions (also known as "impact fees"). This is suggestive as exactions are thought to be a relatively efficient land-use regulation, especially when they help pay for infrastructure improvement (Yinger, 1998). Given the difficulties of measuring regulations as well as the multicollinearity between them, we caution against taking any estimate too literally.

The regression coefficients are positively related to, albeit not identical to, the factor loadings in column 1. 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 may have more limited effects. Indeed, builders may avoid them within a metro area by switching communities. Moreover, the estimated coefficients are based on the economic costs associated with each subindex. Partitioning the coefficient vectors into the regulatory and the geographic, γ^R and γ^G, the predicted value $Z_j^R\hat{\gamma^R}$ provides the cardinal estimate of the costs of regulations, or "Regulatory Cost Index" (RCI).

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-percent reduction in housing costs, respectively.[25]

We take column 4 of table 5 — with factor-neutrality, $\phi^L = 0.33$, σ^Y=0.5, and disaggregated subindices — as our favored specification to construct the RCI. From the cost-share approximation in section 3.1, the cost share of land ranges from 6 percent in Jamestown, NY to 50 percent in New York City. The associated partial elasticities of housing supply, η_j^Y, range from 8.0 to 0.5, with a 99th-percentile of 3.0. Our housing supply elasticities are positively related with those provided by Saiz (2010): a 1-point increase of our elasticity predicts a 1.05-point (s.e. = 0.15) in his.

[25]In appendix table A4, 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.

6 Housing Productivity across Metropolitan Areas

6.1 Productivity in Housing and Tradeables

Column 1 of table 6 lists our inferred measure of housing productivity using both observed and unobserved components of housing productivity (i.e., $\hat{A}^Y_j = -Z_j\gamma_1 - \zeta_j$, assuming $\varepsilon_j = 0$). The cities with the most and least productive housing sectors are McAllen, TX and Santa Cruz, CA. Among large 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, all on California's coast. Along the East Coast, Hartford and Boston are notably unproductive. Cities with approximately average productivity include Miami, Phoenix, and Grand Rapids.[26]

Column 2 reports the estimated RCI, based only on the value of productivity loss predicted by the regulatory subindices, Z^R_j, i.e., $RCI^*_j = Z^R_j \gamma^{R*}_1$. It excludes lost productivity due to geographic restrictions, as well as any unobserved components. The cities with the highest regulatory costs are in New England, notably Manchester, NH; Brockton, MA; and Lawrence, MA-NH; with Boston topping the list of large cities. The West South Central regions has cities with the lowest RCI: New Orleans, LA; Lake Charles, LA; and Little Rock, AR. The differences are also quite suggestive. For example, the regulatory environment in Chicago causes it to be 30 percent more efficient at producing housing than Boston.

Column 3 provides a comparable measure of trade-productivity, following (12), using wages outside of the construction sector, with a value of $\theta_N = 0.85$.[27] Figure 6 plots housing productivity relative to trade-productivity. The figure draws a level curve for total productivity $\hat{A}^{TOT}_j = s^X \hat{A}^X_j + s^Y \hat{A}^Y_j$, which has a slope of $-s^X/s^Y$. The key 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. For instance, coastal cities in California have among the highest levels of trade productivity and the lowest levels of housing productivity. On the other hand, cities like Dallas and Atlanta are relatively more productive in housing than in tradeables. New York, Chicago, Philadelphia, and Las Vegas manage to achieve above average productivity in both sectors.

[26] See appendix table A5 for the values of the major indices and measures for all of the MSAs in our sample.

[27] 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.

6.2 Productivity-Population Gradients in Housing

The negative relationship between trade and housing productivity estimates appears related to city size: while economies of scale in traded goods increase with city size — as expected (e.g., Rosenthal and Strange, 2004) — urban economies of scale in housing seem to be be decreasing. This may arise from technical difficulties in producing housing in crowded, developed areas. Because housing is almost always produced on site, tight spaces around construction sites in crowded environments force builders to use more expensive space-saving technologies. Furthermore, large tracts of land may be more conducive to the mass production of housing.

Furthermore, new construction imposes temporary negative externalities in consumption on incumbent residents. Noise, dust, and safety hazards are greater nuisances in denser environments. Indeed, 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 without directly intending it. This idea is illustrated in figure 7, which plots how the RCI is positively related to population density.

Table 7 examines the relationship of productivity with population levels, aggregated at the consolidated metropolitan (CMSA) level, in panel A, or 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 percent are consistent with many in the literature (Ciccone and Hall 1996, Melo et al. 2009). When trade-productivity $\hat{A}_X^j$ is weighted by its expenditure share, $s^X = 0.64$ in column 4, these elasticities are 3.3 and 3.5 percent. The results in column 2 reveal negative elasticities of housing productivity with respect to population of 6.3 and 5.4 percent; weighted by the expenditure share, $s^Y = 0.16$ in column 5, these are each about negative 1 percent. On net, this means that the total economies of scale in production are reduced to elasticities of 2–3 percent each for population and population density.

Column 3 uses the negative of the RCI, switching signs to be consistent with housing productivity, but excluding biases introduced by correlated geography and various errors in ε_j. The results are more modest but still substantial: a 10-percent increase in population engenders regulations that raise housing costs by roughly 0.25 percent. 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.

6.3 Housing Productivity and Quality of Life

The model in section 3 predicts that if regulations only reduce housing productivity, then they simply reduce welfare. Ostensibly, though, the purpose of land-use regulations is to raise welfare by "recogniz[ing] local externalities, providing amenities that make communities more attractive," (Quigley and Rosenthal, 2005). In this view, sometimes termed the "externality zoning" view, 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).

On the other hand, Hilber and Robert-Nicoud (2013) argue that rent-seeking incentives will cause nicer areas to become more highly regulated, inducing a spurious correlation. Levine (2005) argues that incumbent residents fail to change zoning laws as cities grow, causing inefficiently low density and excess commuting, thereby reducing quality of life. To our knowledge, there are only a few estimates of the 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 study how housing-productivity estimates relate to quality of life indices based on willingness-to-pay measures derived from equation (12). [28] The simple relationship between quality of life and the RCI without amenity controls, is shown in figure 8 and panel A of Table 8. 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 implies that a one-point increase in regulatory costs is associated with a 0.46-point increase in quality of life. Note again that 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.

There are grave problems with interpreting these raw correlations as causal. First, they ignore the likelihood higher quality of life areas may be more prone to regulate. This prob-

[28]The derivation follows Albouy (2008) with some adjustments. We use an expenditure share of 0.16 for housing, and $s^X = 0.64$ as mentioned earlier, for traded goods. For remaining non-housing non-traded goods, the expenditure share is 0.2. The value of $\hat{p}_j + \hat{A}_j^Y$ is used for this non-traded good price, so as to reflect only input costs, because their productivity is unknown, and so as to minimize problems of division bias. The value of $s_w = 0.72$ we use implies a value of $\phi^N = 0.4$, 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.

lem motivates controlling for observable amenities which predict quality of life. Second, the correlations suffer from a potential "division bias": housing productivity is inferred in part from low prices; quality of life, from high prices. As such, measurement error will automatically create a negative bias. We cannot control for this directly, although the RCI should suffer less from this problem than overall productivity.

To control for observable amenities, we estimate the following equation

$$\hat{Q}_j \equiv s^Y \hat{p}_j - s^w \hat{w}_j = \hat{A}_j^{Y*} a + \sum_k q_j^k b_k + e_j \tag{18}$$

where q_j^k refers to individual amenities. The coefficient a provides the elasticity of willingness to pay of households, as a fraction of their income, for housing productivity. 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, as they are highly correlated with housing productivity and the RCI. Columns 2 and 5 include controls for natural amenities, such as climate, adjacency to the coast, and the geographic restriction index. These seemingly exogenous controls virtually eliminate the estimated relationships between quality of life and housing productivity or regulatory costs.

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. Certainly, columns 3 and 6 provide clear evidence that regulations and natural and artificial amenities are positively correlated.

It is worth noting that 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, and hence not show up in willingness-to-pay measures. This problem is endemic to all marginal analysis.

Idiosyncratic benefits are also related to how preference heterogeneity impacts the willingness-to-pay used to estimate quality of life benefits. As explained in subsection 3.3, 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 becomes more of an issue if land-use restrictions reduce the supply of housing by reducing land supply. In the standard

Roback formulation, with homogeneous preferences, simply removing land from development on this "extensive" margin should have no impact on prices in a small open city: land supply does not enter equation (15d). But again, if preferences are heterogeneous, reducing land supply will lower the number of residents in a community, raising willingness-to-pay in ω_{ij} similar to the model of Gyourko et al. (2013).

6.4 Net Effects on Welfare and Land Values

The expenditure share of housing is approximately 0.16, so the social cost of land-use restrictions, expressed as a fraction of total consumption, is equal to 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. In other words, the net benefits are equal to $s^Y + a$.

If we naively accept the simple regression relationship in column 4 of table 8 panel A as causal, it would appear that benefits of regulation are greater than their costs. As discussed above, however, the regulatory environment is highly correlated with both natural and artificial amenities that 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 the the costs they impose on housing production. 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 that regulations which lower housing productivity also reduce social welfare.

Welfare-reducing regulations may persist if quality-of-life benefits accrue to incumbent residents, who control the political process, while the productivity losses are borne by potential residents, who do not have a local political voice. Thus even a small or idiosyncratic quality of life benefit could allow land-use restrictions that reduce overall welfare to persist. Importantly, our results are at the metropolitan level, and could point to a Coasean failure. Potential residents or developers may lack the coordination to buy out the incumbents in particular neighborhoods. As a result, each local community free rides: each could incur a small private cost in quality of life for a large social gain in housing affordability, but chooses not to. As a result, the entire metropolitan area is organized inefficiently.

We conclude by considering the overall effect of productivity and regulations on local land values. This involves running a regression of the form (18), except with $\hat{r_j}$, instead of $\hat{Q}$. Estimates are shown in Panel B. The net welfare loss from regulations implies that land should lose value, despite increases in house prices. This prediction is subject to the same caveat 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.

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 not be causal: it omits the fact that housing productivity is negatively correlated with both quality of life and trade productivity. The latter seems to driven more by artificial amenities than by natural ones, which makes this analysis more circumstantial.

Nevertheless, once we add controls for both natural and artificial amenities, the relationships reverse again. In column 3, we see that housing productivity does appear to boost land values. Column 6 suggests, less precisely, that regulatory costs indeed lower land prices. Given the limited nature of these results, further research is certainly warranted.

The model used in the main analysis assigns all welfare losses to land owners. While preference heterogeneity was of little consequence to our analysis thus far, it can shift the welfare costs partly onto housing consumers. This is easiest to see if consumers are viewed as renters, and land owners as landlords, acknowledging that owner-occupiers effectively rent to themselves. Consumers who have strong tastes for natural amenities or dense cities are more exposed to inefficient housing production. Limited supply causes these households either to be excluded from their preferred community, or to pay prices closer to their reservation value, via a higher marginal ω_{ij}. This increase in willingness boosts land prices that offset (and could even potentially reverse) the negative effects of low housing productivity. Thus, losses to land owners are mitigated, as consumers bear some of the burden.

7 Conclusion

By separating input and output prices for housing, our estimates offer a direct way to isolate how land-use restrictions affect housing prices through supply and demand channels. Our estimates are unique in taking advantage of large variation regulatory and geographic restrictions, as well as land and construction prices.

The estimated cost function fits the data well, passes multiple specification tests, and produces estimates with credible economic magnitudes, despite being drawn from numerous disparate data sources. The two input prices and two restriction measures together explain 87 percent of the variation in home prices. Furthermore, the stability of the land-share estimate and the instrumental variable strategies suggest that the ordinary least squares estimates are likely to be reasonable. Based on the observed price gradients, we estimate the average cost share of land in housing is one-third and, less precisely, that the elasticity of substitution between land and non-land inputs is one-half. These estimates imply that during our time period land's cost share ranged from 6 to 50 percent across metros, e.g., 23 percent in Pittsburgh, 32 percent in Raleigh, 37 percent in Portland, and 48 percent in San Francisco. These varying cost shares help to explain why price elasticities of housing supply differ across cities.

Moreover, the estimates provide strong support for the hypothesis that regulatory and geographic restrictions create a wedge between the prices of housing and its inputs. The disaggregated estimates suggest that state political and court involvement are associated with large increases in housing costs. This is sensible as developers will have the greatest difficulty avoiding wide-ranging regulations. The Regulatory Cost Index quantifies a precise cost of housing regulations, purged of demand factors, which may be useful to other researchers.

Importantly, cities that are productive in traded sectors tend to be less productive in housing, as the two appear to be subject to opposite economies of scale. Larger cities have lower housing productivity, much of which seems attributable to greater regulation. While some regulations may be welfare enhancing, overall these regulatory costs — as measured by our index — have little positive impact on local quality of life once observable amenities are controlled for. Thus, land-use regulations appear to raise housing costs more by restricting supply than by increasing demand. On net, the typical land-use regulation reduces well-being by making housing production less efficient and housing consumption less affordable.

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TABLE 1: MEASURES FOR SELECTED METROPOLITAN AREAS, RANKED BY HOUSING-PRICE DIFFERENTIAL: 2005-2010

Name of Area	Population (1)	Housing Price (2)	Land Value (3)	Const. Price Index (4)	Wages (Const. Only) (5)	Regulation Index (z-score) (6)	Geo Unavail. Index (z-score) (7)
Metropolitan Areas:							
San Francisco, CA PMSA	1,785,097	1.35	1.74	0.24	0.22	1.72	2.14
Santa Cruz-Watsonville, CA PMSA	256,218	1.19	0.69	0.14	0.23	0.82	2.07
San Jose, CA PMSA	1,784,642	1.13	1.47	0.19	0.22	-0.05	1.68
Stamford-Norwalk, CT PMSA	361,024	1.02	1.07	0.14	0.23	-0.56	0.55
Orange County, CA PMSA	3,026,786	0.98	1.32	0.06	0.12	0.08	1.14
Santa Barbara-Santa Maria-Lompoc, CA MSA	407,057	0.97	0.71	0.08	-0.04	0.59	2.76
Los Angeles-Long Beach, CA PMSA	9,848,011	0.92	1.31	0.08	0.12	0.88	1.14
New York, NY PMSA	9,747,281	0.91	1.99	0.29	0.26	-0.17	0.55
Boston, MA-NH PMSA	3,552,421	0.64	0.73	0.18	0.10	1.30	0.24
Washington, DC-MD-VA-WV PMSA	5,650,154	0.41	1.07	-0.03	0.19	0.89	-0.73
Riverside-San Bernardino, CA PMSA	4,143,113	0.26	0.12	0.06	0.12	0.64	0.43
Chicago, IL PMSA	8,710,824	0.19	0.61	0.18	0.07	-0.54	0.53
Philadelphia, PA-NJ PMSA	5,332,822	0.07	0.25	0.16	0.05	0.69	-0.91
Phoenix-Mesa, AZ MSA	4,364,094	0.00	0.41	-0.10	0.00	1.00	-0.73
Atlanta, GA MSA	5,315,841	-0.29	-0.05	-0.08	0.04	0.08	-1.21
Detroit, MI PMSA*	4,373,040	-0.28	-0.33	0.04	-0.02	-0.25	-0.22
Dallas, TX PMSA	4,399,895	-0.43	-0.40	-0.17	0.01	-0.67	-0.96
Houston, TX PMSA	5,219,317	-0.50	-0.30	-0.14	0.04	-0.07	-1.00
Rochester, NY MSA*	1,093,434	-0.53	-1.43	0.03	-0.05	-0.55	0.07
Utica-Rome, NY MSA*	293,280	-0.66	-1.95	-0.03	-0.32	-1.42	-0.55
Saginaw-Bay City-Midland, MI MSA*	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, Ehrlich and Shin (forthcoming) from CoStar COMPS database for years 2005 to 2010. Wage and housing-price data from 2005 to 2010 American Community Survey 1-percent samples. Wage differentials based on the average logarithm of hourly wages. Housing-price differentials 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 Availability 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.

TABLE 2: COST FUNCTION ESTIMATES: THE DEPENDENCE OF METROPOLITAN HOUSING PRICES ON LAND VALUES, CONSTRUCTION PRICES, AND AGGREGATE REGULATORY AND GEOGRAPHIC CONSTRAINTS

Specification	Constrained Cobb-Douglas (1)	Constrained Cobb-Douglas (2)	Unconstrained Cobb-Douglas (3)	Constrained Translog (4)	Constrained Translog (5)	Unconstrained Translog (6)	Constrained Translog w/ Constr Wages (7)	Biased Productivity Constrained Translog (8)
Land-Value Differential	0.470	0.355	0.335	0.463	0.346	0.320	0.341	0.353
	(0.039)	(0.032)	(0.038)	(0.035)	(0.032)	(0.041)	(0.028)	(0.025)
Construction-Price (Wage) Differential	0.530	0.645	1.038	0.537	0.654	0.946	0.659	0.647
	(0.039)	(0.032)	(0.197)	(0.035)	(0.032)	(0.200)	(0.028)	(0.025)
Land-Value Differential Squared				0.069	0.075	0.044	0.062	0.044
				(0.049)	(0.031)	(0.030)	(0.028)	(0.025)
Construction-Price (Wage) Differential Squared				0.069	0.075	-1.506	0.062	0.044
				(0.049)	(0.031)	(1.975)	(0.028)	(0.025)
Land-Value Differential X Construction-Price (Wage) Differential				-0.138	-0.150	0.337	-0.124	-0.088
				(0.098)	(0.062)	(0.371)	(0.056)	(0.050)
Regulatory Index: z-score		0.069	0.065		0.081	0.083	0.058	0.088
		(0.016)	(0.018)		(0.018)	(0.018)	(0.016)	(0.017)
Geographic Index: z-score		0.100	0.093		0.093	0.090	0.108	0.087
		(0.023)	(0.021)		(0.023)	(0.020)	(0.024)	(0.020)
Regulatory Index times (Land Value Differential minus Construction Price Differential)								0.057
								(0.021)
Geographic Index times (Land Value Differential minus Construction Price Differential)								0.019
								(0.034)
Number of Observations	1103	1103	1103	1103	1103	1103	1087	1103
Number of MSAs	230	230	230	230	230	230	228	230
Adjusted R-squared	0.808	0.853	0.859	0.818	0.864	0.870	0.844	0.870
p -value for homogeneity constraints	0.010	0.041		0.083	0.286		0.000	0.153
p -value for CD constraints	0.160	0.017	0.412					
p- value for all constraints	0.002	0.007						
Elasticity of Substitution	1.000	1.000	1.000	0.444	0.333		0.452	0.616
				(0.391)	(0.263)		(0.237)	(0.214)

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 differential coefficients equal zero (the elasticity of substitution between factors equals 1). All regressions include a constant term. Column 7 replaces the construction price with wages in the construction sector.

TABLE 3: COST FUNCTION SENSITIVITY ANALYSES

Specification	Baseline	All-Use Land Values	Unwtd. Land Values	Raw House Prices	2005-2007 Boom Sample	2008-2010 Bust Sample
Dependent Variable	House Price	House Price	House Price	House Price	House Price	House Price
	(1)	(2)	(3)	(4)	(5)	(6)
Land-Value Minus Construction Price Differential	0.346	0.213	0.249	0.381	0.353	0.338
	(0.032)	(0.024)	(0.026)	(0.040)	(0.034)	(0.032)
Land-Value Minus Construction Price Differential Squared	0.075	0.012	0.030	0.036	0.063	0.088
	(0.031)	(0.017)	(0.017)	(0.036)	(0.034)	(0.032)
Regulatory Index: z-score	0.081	0.105	0.116	0.094	0.091	0.071
	(.018)	(.018)	(.015)	(.020)	(.018)	(.019)
Geographic Index: z-score	0.093	0.115	0.093	0.048	0.106	0.080
	(.023)	(.025)	(.028)	(.029)	(.025)	(.022)
Adjusted R-squared	0.864	0.835	0.841	0.831	0.864	0.868
Elasticity of Subsitution	0.333	0.859	0.678	0.691	0.452	0.214
	(0.263)	(0.211)	(0.181)	(0.294)	(0.284)	(0.264)

Robust standard errors, clustered by CMSA, reported in parentheses. Regressions correspond to the restricted specification in column 4 of Table 2. Calibrated specification in column 2 imposes land share of of 23.3 percent and elasticity of substitution of two-thirds, consistent with the calibration in Albouy (2009). All-use land values allow for prediction adjustments based on all land uses, as explained Albouy et al. (forthcoming). 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. Appendix Table A.1 contains sensitivity analyses of the translog model with factor biases.

TABLE 4: INSTRUMENTAL VARIABLES ESTIMATES OF HOUSING COST FUNCTION

Specification	Constrained Cobb-Douglas (1)	Constrained Cobb-Douglas (2)	Constrained Translog (3)	Constrained Translog (4)	Constrained Translog - Limited Instruments (5)	Biased Constrained Translog - Limited IVs (6)
Land-Value Minus Construction Price Differential	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-Value Minus Construction Price Differential Squared			0.007	0.056	0.093	0.010
			(0.086)	(0.044)	(0.038)	(0.106)
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 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)
Regulatory Index times (Land Value Differential minus Construction Price Differential)						0.549
						(0.196)
Geographic Index times (Land Value Differential minus Construction Price						-0.252
						(0.140)
Number of Observations	229	217	229	217	217	217
Adjusted R-squared	0.779	0.764	0.783	0.796	0.797	0.273
Instrument for Land-Value Differential?	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
Elasticity of Substitution	1.000	1.000	0.942	0.535	0.137	0.917
			(0.689)	(0.365)	(0.418)	(0.850)
p-value of Kleibergen-Paap under-identification test	0.019	0.046	0.035	0.018	0.035	0.079
p-value of test of overidentifying restrictions	0.543	0.035	< .001	< .001	0.269	0.569
p-value of test of OLS consistency	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 differential (and differential 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; column3 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 differential and regulatory constraint index from the first-stage regressions as instruments. Tables A2 and A3 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.

TABLE 5: HOUSING COST FUNCTION ESTIMATES WITH DISAGGREGATED REGULATORY AND GEOGRAPHIC RESTRICTION INDICES

Specification	Regulatory Index Factor Loading	Regulatory Index on Subindices	Georaphic Index on Subindices	Constrained Translog
Dependent Variable		Reg Index	Geog Index	Hous. Price
	(1)	(2)	(3)	(4)
Land-Value Minus Construction Price Differential				0.332
				(0.029)
Land-Value Minus Construction Price Differential Squared				0.054
				(0.025)
Approval Delay: z-score	0.29	0.399		0.018
		(0.000)		(0.013)
Local Political Pressure: z-score	0.22	0.332		0.024
		(0.000)		(0.013)
State Political Involvement: z-score	0.22	0.398		0.058
		(0.000)		(0.018)
Open Space: z-score	0.18	0.164		-0.014
		(0.000)		(0.013)
Exactions: z-score	0.15	0.023		-0.022
		(0.000)		(0.014)
Local Project Approval: z-score	0.15	0.167		0.018
		(0.000)		(0.014)
Local Assembly: z-score	0.14	0.124		0.014
		(0.000)		(0.008)
Density Restrictions: z-score	0.09	0.194		0.018
		(0.000)		(0.015)
Supply Restrictions: z-score	0.02	0.087		0.015
		(0.000)		(0.007)
State Court Involvement: z-score	-0.03	-0.059		0.042
		(0.000)		(0.019)
Local Zoning Approval: z-score	-0.04	-0.036		-0.009
		(0.000)		(0.011)
Flat Land Share: z-score			-0.491	-0.084
			(0.034)	(0.022)
Solid Land Share: 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				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).

TABLE 6: INFERRED HOUSING PRODUCTIVITY, REGULATORY COST, AND OTHER 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 PMSA	-0.902	0.095	0.177
San Francisco, CA PMSA	-0.527	0.187	0.182
San Jose, CA PMSA	-0.455	0.037	0.182
Orange County, CA PMSA	-0.437	0.060	0.080
Bergen-Passaic, NJ PMSA	-0.376	0.024	0.136
Los Angeles-Long Beach, CA PMSA	-0.385	0.121	0.080
Boston, MA-NH PMSA	-0.284	0.213	0.086
Washington, DC-MD-VA-WV PMSA	-0.035	0.047	0.119
Phoenix-Mesa, AZ MSA	0.041	0.128	-0.002
New York, NY PMSA	0.076	0.006	0.136
Philadelphia, PA-NJ PMSA	0.088	-0.007	0.059
Chicago, IL PMSA	0.114	-0.092	0.053
Dallas, TX PMSA	0.144	-0.094	-0.002
Atlanta, GA MSA	0.184	-0.011	-0.002
Detroit, MI PMSA*	0.165	0.031	0.002
Houston, TX PMSA	0.272	-0.071	0.017
Las Vegas, NV-AZ MSA	0.320	-0.122	0.061
McAllen-Edinburg-Mission, TX MSA	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 infrred housring 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 differential. Refer to section 3.3 of the text for the calculation of quality-of-life estimates. Quality of life and total amenity value are expressed as a fraction of average pre-tax household income.

TABLE 7: URBAN ECONOMIES AND DISECONOMIES OF SCALE: THE RELATIONSHIP OF TRADE AND HOUSING PRODUCTIVITIES WITH METROPOLITAN POPULATION AND DENSITY

	Dependent Variable						
				Weighted Productivities			
	Trade Productivity (1)	Housing Productivity (2)	Minus Regulatory Cost Index (3)	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)
Number of Observations	230	230	230	230	230	230	230
Adjusted R-squared	0.653	0.145	0.116	0.653	0.145	0.502	0.618
Panel B: Population Density							
Weighted Density Differential	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)
Number of Observations	230	230	230	230	230	230	230
Adjusted R-squared	0.386	0.053	0.066	0.386	0.053	0.349	0.366

Robust standard errors, clustered by CMSA, reported in parentheses. Trade and housing productivity differentials 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 differential 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.

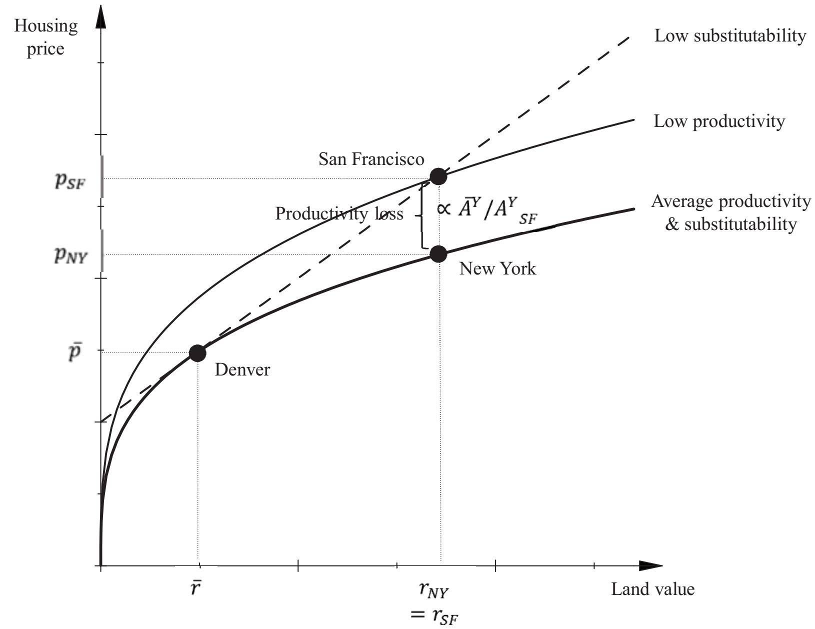
TABLE 8: THE WELFARE CONSEQUENCES OF LAND-USE REGULATION: THE RELATIONSHIP OF QUALITY OF LIFE AND LAND VALUES WITH HOUSING PRODUCTIVITY

	(1)	(2)	(3)	(4)	(5)	(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 Amenties		X	X		X	X
Controls for Artificial Amenties			X			X
Number of Observations	230	225	216	230	225	216

Robust standard errors, clustered by CMSA, in parentheses. Quality of life and regulatory cost index are calculated as 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. (2012) and Albouy (2016). Elasticity of Social Welfare is calculated as expenditure share of housing, 0.18, plus elasticity of Quality of Life with respect to Housing Productivity or the negative of the RCI.

Figure 1: The Effects of Low Productivity or Low Substitutability on Housing Prices

(a) Levels



(b) Logarithms

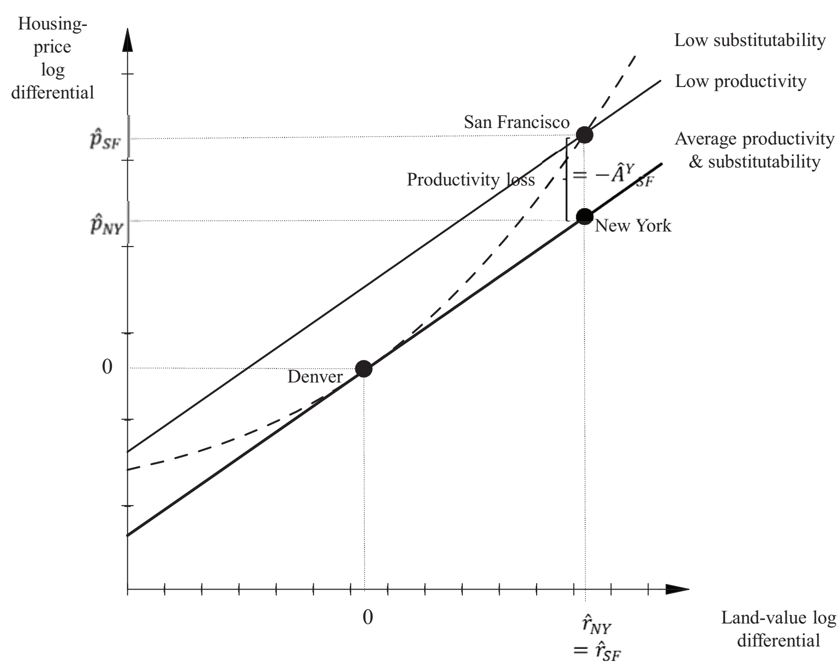


Figure 2: House Prices vs. Land Values

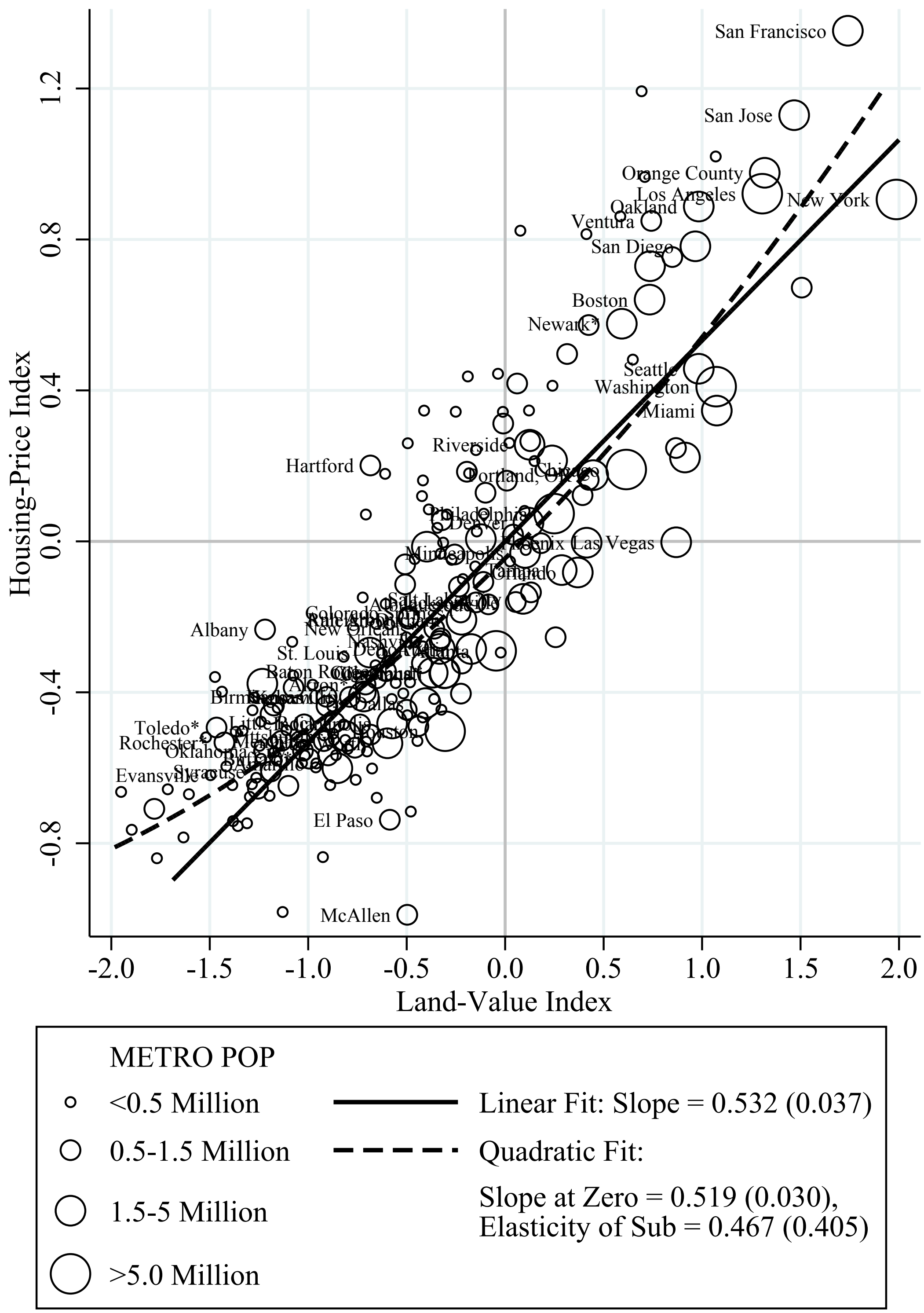
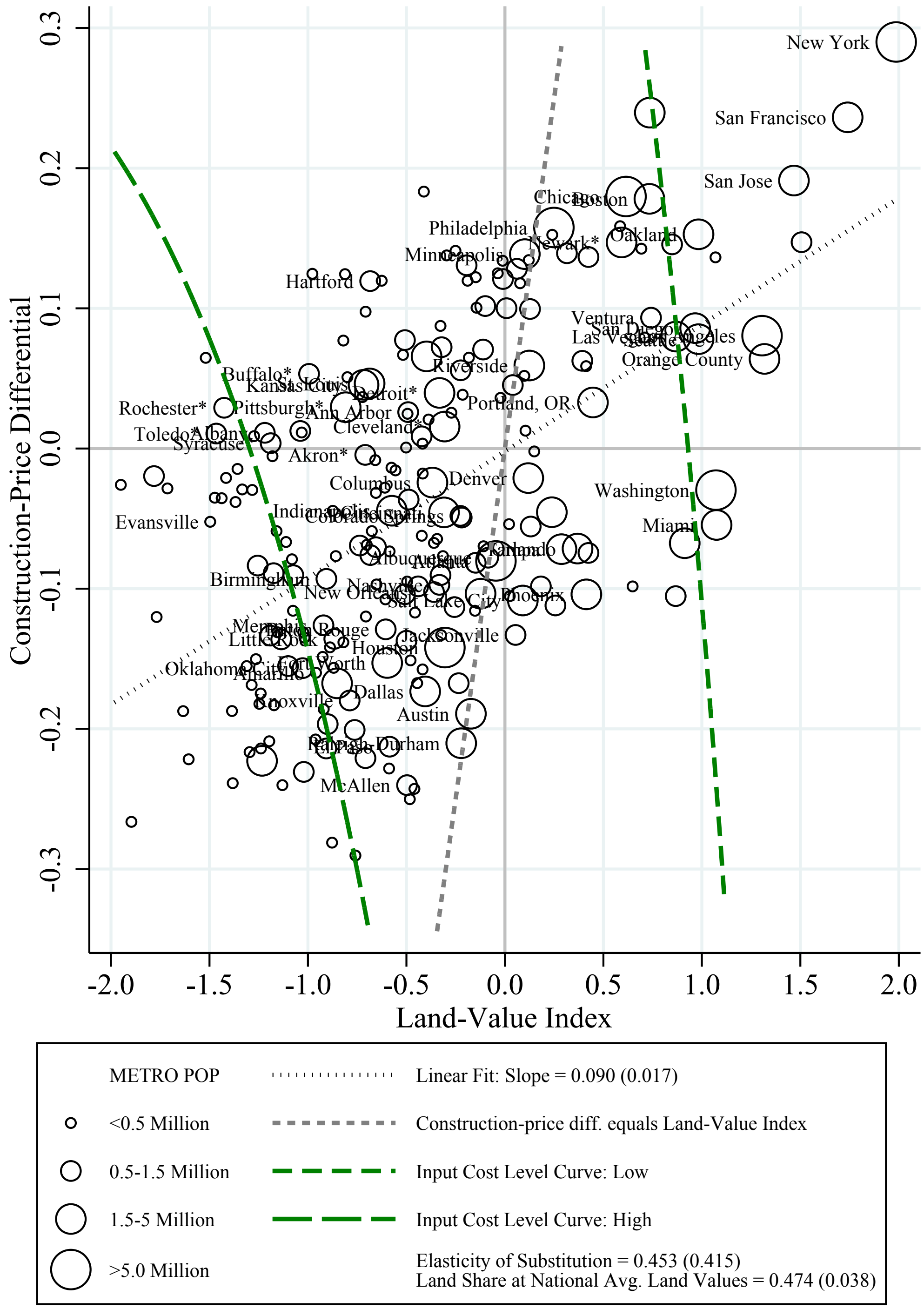


Figure 3: Construction Prices vs. Land Values



Note: Input cost level curves plot combinations of construction-price differentials and land value indexes that produce housing costs 50 percent 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.

Figure 4: Housing Cost Surface with $\phi_L = 0.47$ and $\sigma^Y = 0.45$

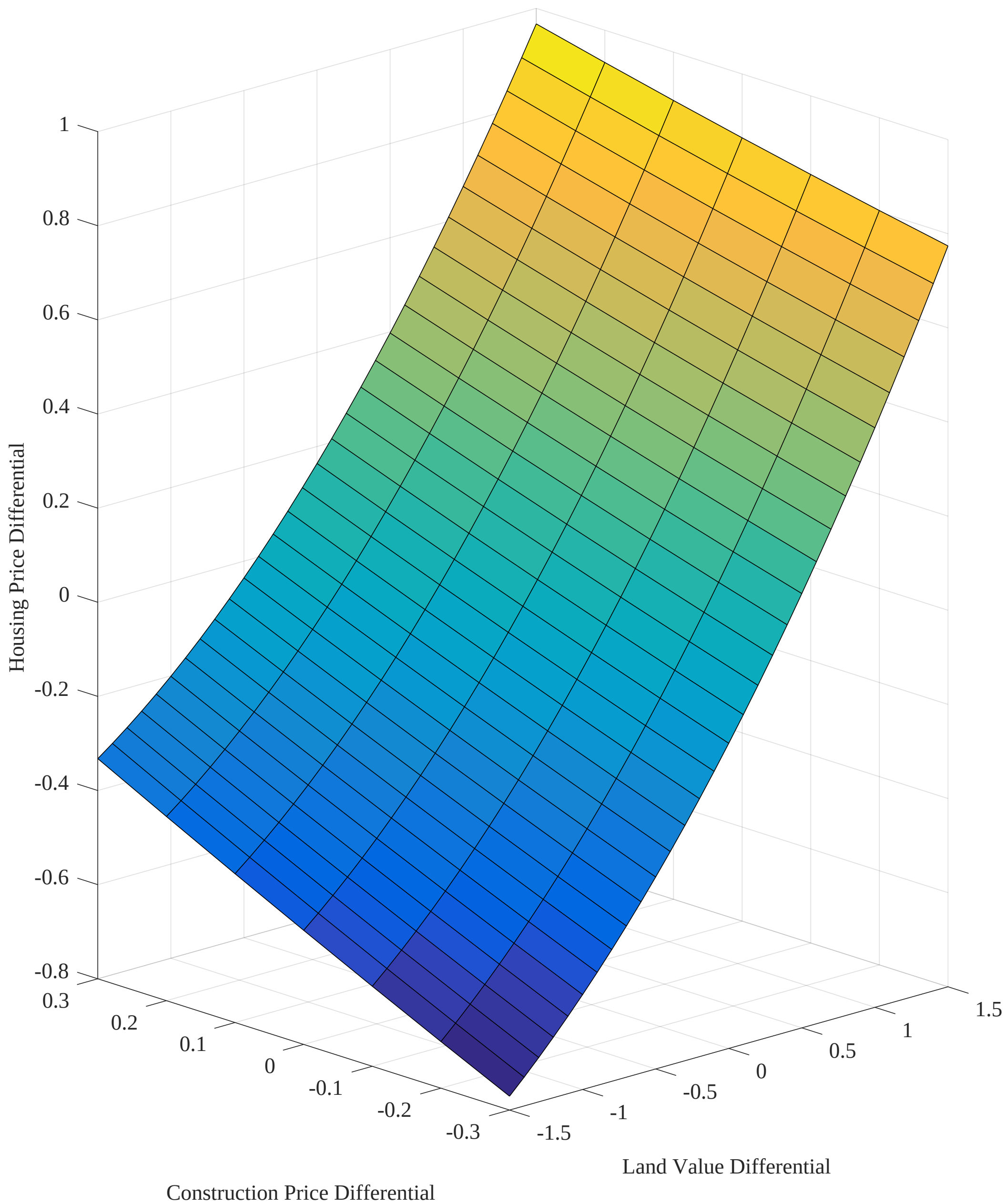
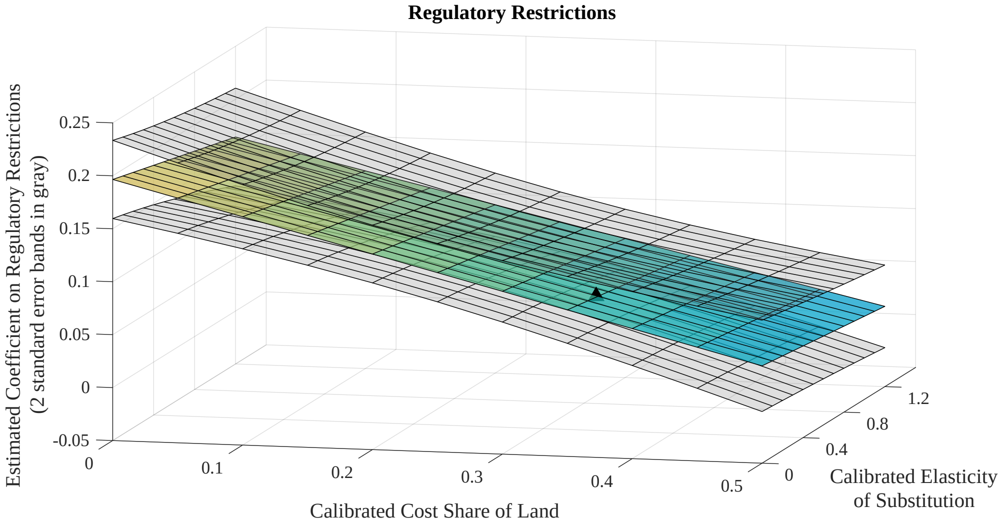
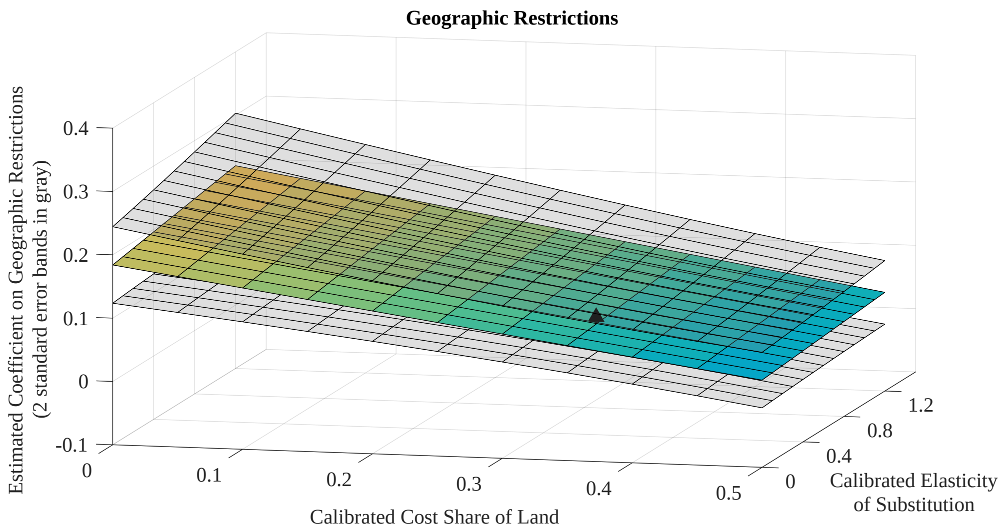


Figure 5: Estimated Effects of Restrictions on Housing Productivity





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.

Figure 6: Productivity in the Tradeable and Housing Sectors

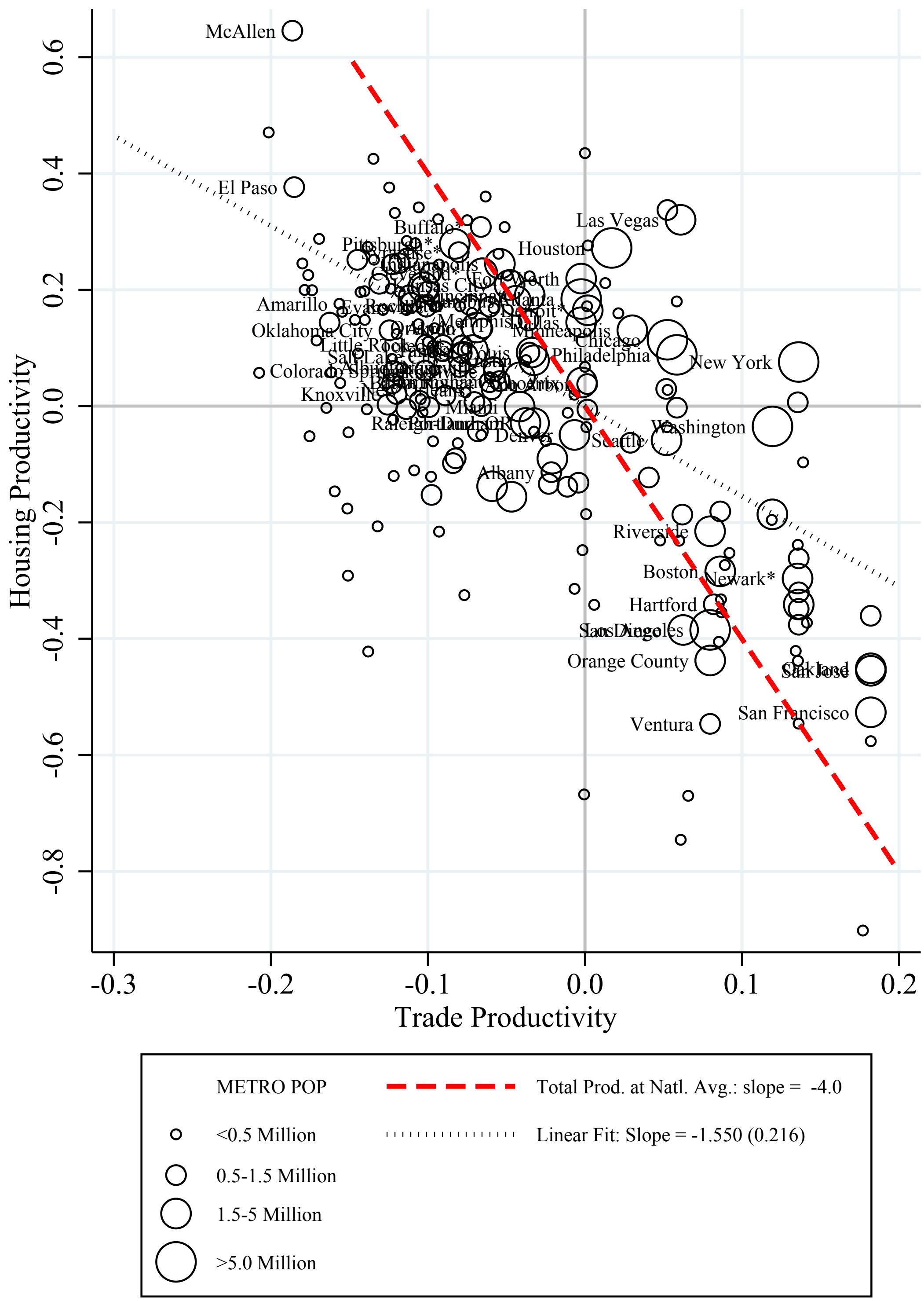


Figure 7: Regulatory Cost Index vs. Log Population Density

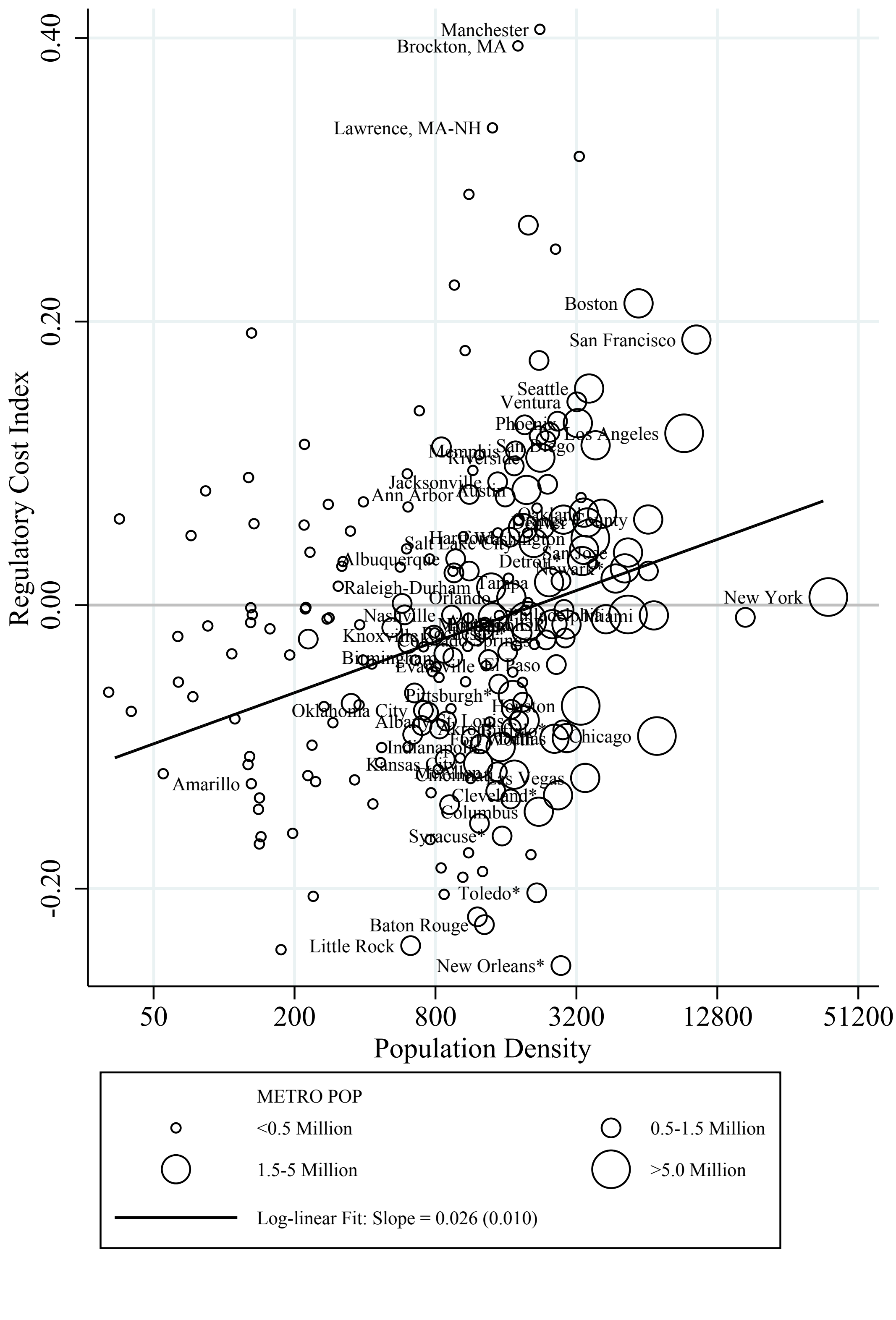
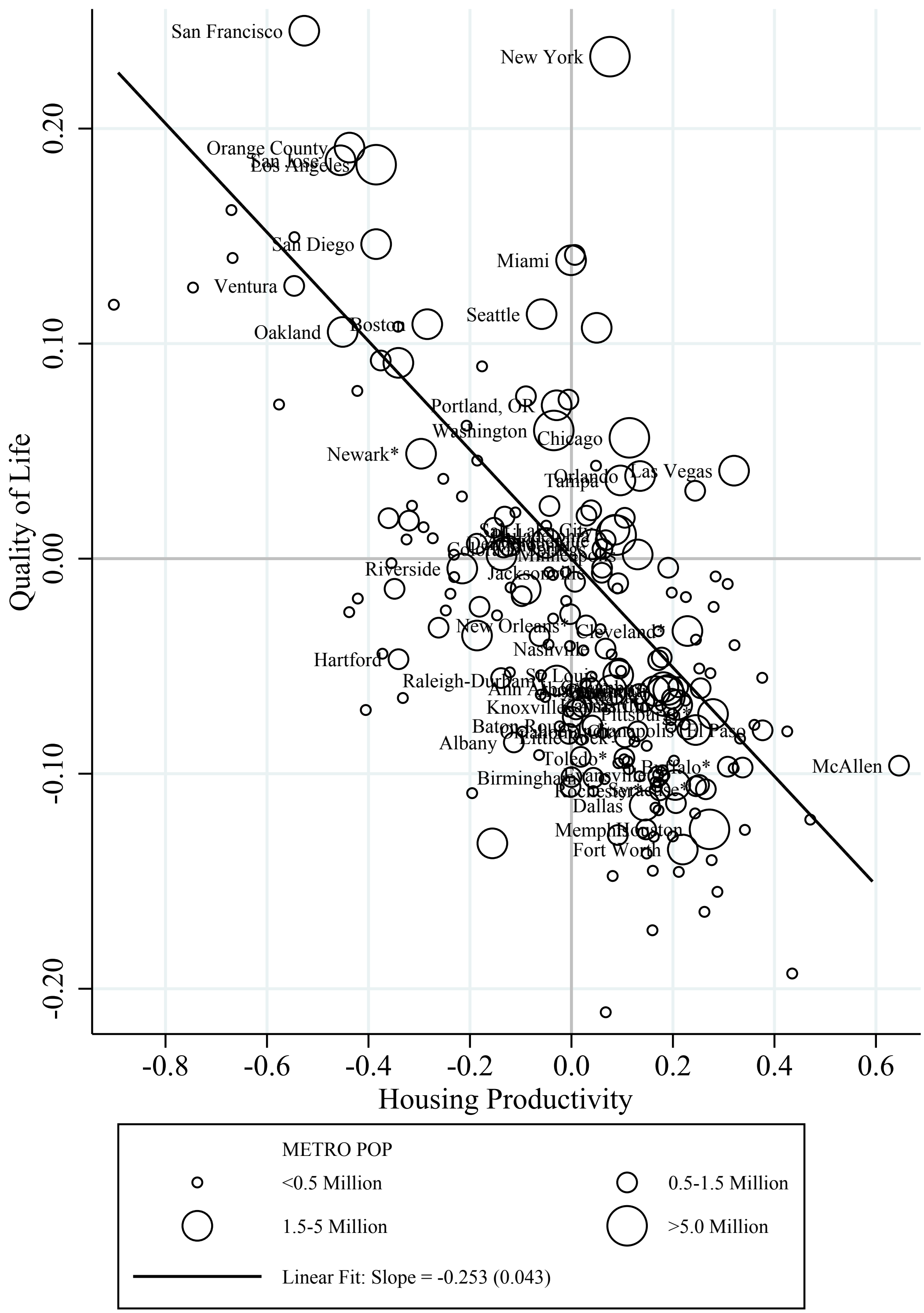


Figure 8: Quality of Life vs. Housing Productivity



Appendix for Online Publication Only

A Housing Productivity and Factor Bias

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

To simplify the notation, consider efficiency units of land and materials, $L^* \equiv A_j^{YL}L, M^* \equiv A_j^{YM}M$. The prices of these efficiency units are $\tilde{r} \equiv r/A^{YL}, v^* = v/A^{YM}$. Further, drop the subscripts on the prices and the superscripts Y. 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 Shepard's Lemma, the first derivatives of the cost function with respect to the first and second argument 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:

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

Assuming the equilibrium condition $\ln p = \ln c = \ln c^*$ holds, then we have the first-order approximation:

$$\hat{p}_j = \phi^L \hat{r}^* + \phi^M \hat{v}^* = \phi^L \hat{r}_j + \phi^M \hat{v}_j \underbrace{-\phi^L \hat{A}_j^L - \phi^M \hat{A}_j^{ML}}_{-\hat{A}_j^Y} \tag{A.5}$$

The first-order approximation is Cobb-Douglas, and does not allow us to disentangle factor bias as both $\hat{A}_j^L$ and $\hat{A}_j^M$ 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

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

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

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

Of course, the second-order pure derivatives are the first-order derivatives of the function describing the cost shares. Thus, the first order expression for ϕ_L^j follows directly from a first-order Taylor expansion in r^* and v^*

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

which is equation (5) in the main text. When $\sigma = 1$, the cost share does not change. 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 a fairly straightforward second-order log-linear approximation of the cost function:

$$\begin{aligned}\hat{c}_j &= \phi^L(\hat{r}_j - \hat{A}_j^L) + (1-\phi^L)(\hat{v}_j - \hat{A}_j^L) \\ &\quad + (1/2)\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{v}_j - \hat{A}_j^L + \hat{A}_j^M)^2 \\ &= \phi^L \hat{r}_j + (1-\phi^L)\hat{v}_j + (1/2)\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{v}_j - \hat{B}_j)^2 + \hat{A}_j\end{aligned}$$

This provides the formulation in equation (4) 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 differential, creates the series of terms

$$\hat{p}_j - \hat{v}_j = \phi^L(\hat{r}_j - \hat{v}_j) \tag{A.10a}$$
$$+ (1/2)\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{v}_j)^2 \tag{A.10b}$$
$$+ Z_j\delta_A \tag{A.10c}$$
$$+ \xi_{Aj} \tag{A.10d}$$
$$+ \phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{v}_j)Z_j\delta_B \tag{A.10e}$$
$$+ (1/2)\phi^L(1-\phi^L)(1-\sigma^Y)(Z_j\delta_B)^2 \tag{A.10f}$$
$$+ \xi_{Bj}\phi^L(1-\phi^L)(1-\sigma^Y)(Z_j\delta_B + \hat{r}_j - \hat{v}_j + \xi_{Bj}/2) \tag{A.10g}$$

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 differentials, $\hat{r}_j$ and $\hat{v}_j$. Thus, it is best to leave and the remaining terms, in an error term along with (A.10g).

Based on the above discussion, we collect the coefficients as

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

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

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

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

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

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

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

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

The constrained model provides a number of testable coefficient constraints:

$$\beta_1 = 1 - \beta_2 \quad \text{(A.14a)}$$

$$\beta_3 = \beta_4 \quad \text{(A.14b)}$$

$$\beta_3 = -\beta_5/2 \quad \text{(A.14c)}$$

$$\gamma_2 = -\gamma_3 \quad \text{(A.14d)}$$

The first three of which apply to the standard cost function, while the fourth applies only to factor bias.[29]

To obtain the elasticity of supply, take the differentials of Shepard's Lemma for land from (A.3):

$$\hat{L} + \hat{A}^L - \hat{Y} = d \ln c_r^* \quad \text{(A.15)}$$

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

where the last line obtains from a first-order approximation. Now, from the first-order equilibrium condition for housing costs, (A.5), it follows from $\phi^M = 1 - \phi^L$:

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

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

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

The partial equilibrium formula in (1) comes from simply considering changes in p without considering general equilibrium feedbacks.

The derivation of the estimate of trade productivity in equation (13), 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

[29] It is possible to test if the elasticity of substitution varies with Z^j by adding the term $\left(\hat{r}_j - \hat{v}_j\right)^2 Z^j \gamma_3$. 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.

(12) follows from

$$\frac{\partial \ln(w+I)}{\partial \ln w} = \frac{w}{w+I} \equiv s_w$$
$$\frac{\partial \ln e}{\partial \ln p} = \frac{py}{e} \equiv s_y$$
$$\frac{\partial \ln e}{\partial \ln Q} = \frac{Q}{e}\frac{\partial e}{\partial Q} = 1$$

where the last line follows from the normalization of Q described in section 3.3.

B Wage and Housing Price Indices

The wage and housing price indices are estimated from the 2005 to 2010 American Community Survey, which samples 1% of the United States population every year. The indices are estimated with separate regressions for each year. For the wage regressions, we include all workers who live in an MSA and were employed in the last year, and reported positive wage and salary income. We calculate hours worked as average weekly hours times the midpoint of one of six bins for weeks worked in the past year. We then divide wage and salary income for the year by our calculated hours worked variable to find an hourly wage. We regress the log hourly wage on a set of MSA dummies and a number of individual covariates, each of which is interacted with gender:

- 16 indicators of educational attainment;
- a quartic in potential experience and potential experience interacted with years of education;
- 9 indicators of industry at the one-digit level (1950 classification);
- 9 indicators of employment at the one-digit level (1950 classification);
- 5 indicators of marital status (married with spouse present, married with spouse absent, divorced, widowed, separated);
- an indicator for veteran status, and veteran status interacted with age;
- 5 indicators of minority status (Black, Hispanic, Asian, Native American, and other);
- an indicator of immigrant status, years since immigration, and immigrant status interacted with black, Hispanic, Asian, and other;
- 2 indicators for English proficiency (none or poor).

This regression is first run using census-person weights. From the regressions a predicted wage is calculated using individual characteristics alone, controlling for MSA, to form a new weight equal to the predicted wage times the census-person weight. These new income-adjusted weights allow us to weight workers by their income share. The new weights are then used in a second regression, which is used to calculate the city-wage indices from the MSA indicator variables, renormalized to have a national average of zero every year. In practice, this weighting procedure has only a small effect. The wage regressions are at the CMSA, rather than PMSA, level to reflect the ability of workers to commute to jobs throughout a CMSA.

The traded sector wage differentials are calculated excluding workers with occupations in the construction trades. To calculate construction wage differentials, we drop all non-construction workers and follow the same procedure as above. We define the construction sector as occupation codes 620 through 676 in the ACS occupation codes. In our sample, 4.5% of all workers are in the construction sector.

As noted in section 4.1, the construction price index is taken from RS Means company. For each city in the sample, RS Means reports construction costs for a composite of nine common structure types. The index reflects the costs of labor, materials, and equipment rental, but not cost variations from regulatory restrictions, restrictive union practices, or regional differences in building codes. We renormalize this index as a $z-$score with an average value of zero and a standard deviation of one across cities.[30]

The housing price index of an MSA is calculated in a manner similar to the differential wage, by regressing housing prices for owner-occupied units on a set of covariates. The covariates used in the regression for the adjusted housing cost differential are:

- 10 indicators of building size;
- 9 indicators for the number of rooms, 5 indicators for the number of bedrooms, and number of rooms interacted with number of bedrooms;
- 2 indicators for lot size;
- 9 indicators for when the building was built;
- 2 indicators for complete plumbing and kitchen facilities;
- an indicator for commercial use;
- an indicator for condominium status.

[30]The RS Means index covers cities as defined by three-digit zip code locations, and as such there is not necessarily a one-to-one correspondence between metropolitan areas and RS Means cities. In cases in which there is more than one three-digit zip code with a construction cost listed for an MSA, we weight the zip codes by the number of housing units in each zip code in the year 2000. We only have the 2010 edition of the RS Means index.

A regression of housing values on housing characteristics and MSA indicator variables is first run weighting by census-housing weights. A new value-adjusted weight is calculated by multiplying the census-housing weights by the predicted value from this first regression using housing characteristics alone, controlling for MSA. A second regression is run using these new weights on the housing characteristics, along with the MSA indicators. The housing-price indices are taken from the MSA indicator variables in this second regression, renormalized to have a national average of zero every year. As with the wage differentials, this adjusted weighting method has only a small impact on the price differentials. In contrast to the wage regressions, the housing price regressions were run at the PMSA level to achieve a better geographic match between the housing stock and the underlying land.

TABLE A1: INSTRUMENTAL VARIABLES ESTIMATES, FIRST-STAGE REGRESSIONS

Dependent Variable	Land Rent minus Construction Price (1)	Land Rent minus Construction Price (2)	Regulatory Index: z-score (3)	Land Rent minus Construction Price (4)	Land Rent minus Construction Price Squared (5)	Land Rent minus Construction Price (6)	Land Rent minus Construction Price Squared (7)	Regulatory Index: z-score (8)
Geographic Constraint Index: z-score	0.091	0.038	-0.072	0.108	-0.052	0.115	-0.026	-0.030
	(0.084)	(0.080)	(0.097)	(0.098)	(0.074)	(0.089)	(0.071)	(0.094)
Regulatory Constraint Index: z-score	0.187			0.184	-0.139			
	(0.064)			(0.053)	(0.057)			
Inverse of Mean Distance from Sea: z-score	0.309	0.314	0.120	0.262	0.019	0.212	-0.049	0.227
	(0.072)	(0.068)	(0.078)	(0.167)	(0.125)	(0.160)	(0.149)	(0.136)
USDA Amenities Score: z-score	0.074	0.097	0.172	0.048	-0.048	0.068	-0.065	0.247
	(0.031)	(0.029)	(0.033)	(0.034)	(0.031)	(0.033)	(0.029)	(0.046)
Non-traditional Christian Share (1971): z-score		-0.116	-0.333			-0.189	-0.025	-0.540
		(0.050)	(0.077)			(0.054)	(0.062)	(0.109)
Protective Inspections Share (1980): z-score		0.118	-0.056			0.187	-0.101	-0.021
		(0.048)	(0.096)			(0.054)	(0.063)	(0.075)
Inverse of Mean Distance from Sea: z-score squared				0.012	0.124	-0.034	0.136	-0.155
				(0.047)	(0.039)	(0.048)	(0.051)	(0.051)
USDA Amenities Score: z-score squared				0.014	0.038	0.009	0.032	-0.029
				(0.006)	(0.009)	(0.006)	(0.011)	(0.013)
Inverse of Mean Distance from Sea: z-score times USDA Amenities Score: z-score				-0.044	0.003	-0.032	-0.010	0.009
				(0.010)	(0.010)	(0.013)	(0.016)	(0.024)
Inverse of Mean Distance from Sea: z-score times Non-traditional Christian Share (1971): z-score						-0.218	-0.011	-0.325
						(0.081)	(0.081)	(0.141)
USDA Amenities Score: z-score times Non-traditional Christian Share (1971): z-score						-0.030	-0.043	0.028
						(0.027)	(0.034)	(0.052)
Inverse of Mean Distance from Sea: z-score times Protective Inspections Share (1980): z-score						0.013	0.078	0.083
						(0.063)	(0.088)	(0.099)
USDA Amenities Score: z-score times Protective Inspections Share (1980): z-score						-0.054	0.036	-0.071
						(0.021)	(0.025)	(0.035)
Number of Observations	229	217	217	229	229	217	217	217
Adjusted R-squared	0.558	0.548	0.264	0.578	0.364	0.609	0.370	0.342
F-statistic of Excluded Instruments	9.4	14.8	18.0	25.8	29.9	44.1	55.0	14.4
First Stage Regression for the these specifications in Table 5:	Column 1	Column 2	Column 2	Column 3	Column 3	Column 4	Column 4	Column 4

Robust standard errors, clustered by CMSA, reported in parentheses. See Table 4 for variable descriptions and data sources. All regressions are first stages for second-stage regressions reported in coulmns 1 through 4 of Table 4.

TABLE A2: INSTRUMENTAL VARIABLES ESTIMATES, FIRST-STAGE REGRESSIONS - LIMITED INSTRUMENTS

Dependent Variable	Land Rent minus Construction Price (1)	Land Rent minus Construction Price Squared (2)	Regulatory Index: z-score (3)	Land Rent minus Construction Price (4)	Land Rent minus Construction Price Squared (5)	Regulatory Index: z-score (6)	Land Rent minus Construction Price times Geographic Constraint Index (7)	Land Rent minus Construction Price times Regulatory Index (8)
Geographic Constraint Index: z-score	0.042	-0.049	-0.058	0.007	-0.076	-0.047	-0.030	0.007
	(0.080)	(0.070)	(0.089)	(0.073)	(0.073)	(0.093)	(0.066)	(0.062)
Inverse of Mean Distance from Sea: z-score	0.366	0.044	0.298	0.440	0.021	0.371	-0.087	-0.030
	(0.084)	(0.078)	(0.085)	(0.091)	(0.090)	(0.091)	(0.064)	(0.078)
USDA Amenities Score: z-score	0.101	0.003	0.186	0.076	0.004	0.165	0.015	-0.032
	(0.030)	(0.032)	(0.031)	(0.028)	(0.027)	(0.040)	(0.025)	(0.028)
Non-traditional Christian Share (1971): z-score	-0.118	-0.074	-0.342	-0.140	-0.135	-0.307	-0.089	0.012
	(0.051)	(0.052)	(0.074)	(0.049)	(0.059)	(0.075)	(0.048)	(0.058)
Protective Inspections Share (1980): z-score	0.113	-0.119	-0.076	0.169	-0.106	-0.072	-0.004	-0.106
	(0.047)	(0.069)	(0.094)	(0.050)	(0.060)	(0.095)	(0.043)	(0.076)
Predicted Land Rent minus Construction Price Squared	-0.179	0.799	-0.613	-0.708	1.095	-1.312	0.017	-0.578
	(0.132)	(0.310)	(0.363)	(0.499)	(0.775)	(0.511)	(0.335)	(0.316)
Predicted Land Rent minus Construction Price times Predicted Regulatory Constraint Index				1.042	-0.013	0.512	0.643	0.851
				(0.362)	(0.627)	(0.489)	(0.293)	(0.305)
Predicted Land Rent minus Construction Price times Geographic Constraint Index				-0.194	-0.178	0.223	0.579	0.461
				(0.148)	(0.186)	(0.199)	(0.139)	(0.126)
Number of Observations	217	217	217	217	217	217	217	217
Adjusted R-squared	0.552	0.288	0.295	0.594	0.312	0.304	0.590	0.157
F-statistic of Excluded Instruments	12.2	7.7	14.6	14.3	8.1	11.5	20.8	10.0
First Stage Regression for the these specifications in Table 5:	Column 5	Column 5	Column 5	Column 6	Column 6	Column 6	Column 6	Column 6

Robust standard errors, clustered by CMSA, reported in parentheses. See Table 4 for variable descriptions and data sources. All regressions are first stages for second-stage regressions reported in coulmns 5 and 6 of Table 4.

TABLE A3: CALIBRATED IV COST FUNCTION ESTIMATES

Specification	Calibrated 2SLS	Calibrated 2SLS	Calibrated 2SLS	Calibrated 2SLS
Dependent Variable	House Price	House Price	House Price	House Price
	(1)	(2)	(3)	(4)
Regulatory Index: z-score	0.121	0.121	0.071	0.072
	(0.028)	(0.033)	(0.021)	(0.027)
Geographic Index: z-score	0.161	0.192	0.037	0.079
	(0.056)	(0.068)	(0.047)	(0.059)
Adjusted R-squared	0.685	0.667	0.690	0.706
Land-Value Minus Construction				
Price Differential	0.233	0.233	0.433	0.433
Elasticity of Subsitution	0.000	1.000	0.000	1.000

Robust standard errors, clustered by CMSA, reported in parentheses. All regression specifications correspond to the constrained specification in column 4 of Table 4, and instrument for the Wharton Residential Land Use Regulatory Index using the nontraditional Christian share in 1971 and the share of local expenditures devoted to protective inspections in 1982.

TABLE A4: HOUSING COST FUNCTION ESTIMATES WITH DISAGGREGATED REGULATORY AND GEOGRAPHIC RESTRICTION INDICES AND NON-NEUTRAL PRODUCTIVITY INTERACTIONS

Specification	Base Coefficients	Interacted with Land-Value Diff. minus Cons. Price Diff.
Dependent Variable	House Prices (1)	
Land-Value Minus Construction Price Differential	0.329	
	(0.025)	
Land-Value Minus Construction Price Differential Squared	0.049	
	(0.019)	
Approval Delay: z-score	0.026	-0.018
	(0.015)	(0.021)
Local Political Pressure: z-score	0.008	-0.020
	(0.010)	(0.022)
State Political Involvement: z-score	0.056	0.027
	(0.018)	(0.025)
Open Space: z-score	-0.022	-0.032
	(0.017)	(0.026)
Exactions: z-score	-0.015	0.017
	(0.014)	(0.017)
Local Project Approval: z-score	0.038	0.066
	(0.016)	(0.023)
Local Assembly: z-score	0.012	-0.004
	(0.010)	(0.019)
Density Restrictions: z-score	0.033	0.018
	(0.017)	(0.019)
Supply Restrictions: z-score	0.024	0.027
	(0.007)	(0.012)
State Court Involvement: z-score	0.018	-0.024
	(0.021)	(0.027)
Local Zoning Approval: z-score	-0.013	0.000
	(0.014)	(0.017)
Flat Land Share: z-score	-0.081	-0.065
	(0.023)	(0.024)
Solid Land Share: z-score	-0.069	-0.049
	(0.020)	(0.020)
Number of Observations	1,103	
Adjusted R-squared	0.910	
Elasticity of Substitution	0.558	
	(0.169)	

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).

TABLE A5: ALL METROPOLITAN INDICES RANKED BY HOUSING PRICE DIFFERENTIAL, 2005-2010

			Adjusted Differentials					*Raw Differentials*				*Productivity*			
Full Name	Population	Census Division	Land Value	Land Value (All Uses)	Land Value (Un-wtd.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Unavail. Index (z-score)	Const. Price Index	Housing	Tradeables	Regulatory Cost Index	Housing Price Rank
Metropolitan Areas:															
San Francisco, CA PMSA	1,785,097	9	1.740	2.613	1.904	1.353	0.216	0.223	1.716	2.137	0.236	-0.527	0.182	0.187	1
Santa Cruz-Watsonville, CA PMSA	256,218	9	0.693	0.951	0.975	1.193	0.213	0.233	0.820	2.072	0.143	-0.902	0.177	0.095	2
San Jose, CA PMSA	1,784,642	9	1.468	1.565	1.854	1.129	0.216	0.222	-0.054	1.684	0.191	-0.455	0.182	0.037	3
Stamford-Norwalk, CT PMSA	361,024	1	1.069	1.405	1.727	1.020	0.175	0.229	-0.564	0.551	0.136	-0.546	0.136	0.002	4
Orange County, CA PMSA	3,026,786	9	1.318	1.612	2.245	0.977	0.100	0.122	0.078	1.135	0.064	-0.437	0.080	0.060	5
Santa Barbara-Santa Maria-Lompoc, CA MSA	407,057	9	0.709	1.042	0.856	0.966	0.053	-0.037	0.588	2.761	0.079	-0.670	0.066	0.071	6
Los Angeles-Long Beach, CA PMSA	9,848,011	9	1.306	1.825	1.614	0.921	0.100	0.123	0.883	1.135	0.081	-0.385	0.080	0.121	7
New York, NY PMSA	9,747,281	2	1.987	3.358	2.714	0.906	0.180	0.256	-0.166	0.551	0.290	0.076	0.136	0.006	8
Oakland, CA PMSA	2,532,756	9	0.983	1.186	1.374	0.887	0.216	0.222	0.589	1.581	0.153	-0.451	0.182	0.064	9
Santa Rosa, CA PMSA	472,102	9	0.585	0.140	0.428	0.861	0.216	0.222	1.322	1.646	0.159	-0.576	0.182	0.226	10
Ventura, CA PMSA	802,983	9	0.742	0.328	0.810	0.849	0.100	0.123	1.701	2.452	0.093	-0.546	0.080	0.143	11
Salinas, CA MSA	410,370	9	0.077	0.097	0.219	0.823	-0.004	-0.292	-0.021	1.797	0.118	-0.746	0.061	0.076	12
San Luis Obispo-Atascadero-Paso Robles, CA MSA	266,971	9	0.413	0.750	1.291	0.814	-0.007	-0.031	1.435	1.783	0.059	-0.668	-0.001	0.192	13
San Diego, CA MSA	3,053,793	9	0.966	1.075	0.431	0.782	0.079	0.099	0.987	1.666	0.086	-0.385	0.063	0.113	14
Bergen-Passaic, NJ PMSA	1,387,028	2	0.849	1.270	1.550	0.753	0.180	0.256	0.366	0.551	0.146	-0.376	0.136	0.024	15
Nassau-Suffolk, NY PMSA	2,875,904	2	0.736	0.587	1.300	0.729	0.180	0.256	0.854	0.551	0.240	-0.341	0.136	-0.010	16
Jersey City, NJ PMSA	597,924	2	1.506	2.009	2.580	0.672	0.181	0.263	-0.534	0.231	0.147	0.007	0.136	-0.009	17
Boston, MA-NH PMSA	3,552,421	1	0.734	0.908	0.662	0.641	0.101	0.101	1.301	0.236	0.178	-0.284	0.086	0.213	18
Newark, NJ PMSA	2,045,344	2	0.592	0.993	0.485	0.577	0.181	0.263	0.057	0.071	0.147	-0.296	0.135	0.026	19
Vallejo-Fairfield-Napa, CA PMSA	541,884	9	0.424	0.114	0.389	0.573	0.216	0.222	0.895	0.975	0.137	-0.361	0.182	0.112	20
Middlesex-Somerset-Hunterdon, NJ PMSA	1,247,641	2	0.315	-0.020	0.453	0.497	0.180	0.256	2.208	0.551	0.139	-0.320	0.136	0.085	21
Naples, FL MSA	318,537	5	0.648	0.441	0.500	0.482	-0.037	-0.201	0.176	2.257	-0.098	-0.342	0.006	-0.043	22
Seattle-Bellevue-Everett, WA PMSA	2,692,066	9	0.983	1.271	0.779	0.457	0.056	0.039	1.675	0.707	0.078	-0.059	0.052	0.153	23
Danbury, CT PMSA	223,095	1	-0.036	-0.108	0.153	0.444	0.177	0.249	-0.527	0.551	0.125	-0.421	0.134	0.137	24
Bridgeport, CT PMSA	470,094	1	-0.190	0.232	0.583	0.437	0.178	0.249	0.353	0.551	0.120	-0.438	0.136	0.029	25
Monmouth-Ocean, NJ PMSA	1,217,783	2	0.061	-0.140	0.212	0.418	0.180	0.255	2.095	0.551	0.128	-0.349	0.136	0.098	26
Lowell, MA-NH PMSA	310,264	1	0.240	0.119	0.498	0.412	0.106	0.098	2.001	0.236	0.152	-0.253	0.092	0.316	27
Washington, DC-MD-VA-WV PMSA	5,650,154	5	1.071	1.599	0.662	0.410	0.150	0.187	0.892	-0.731	-0.030	-0.035	0.119	0.047	28
Trenton, NJ PMSA	366,222	2	0.121	-0.160	0.281	0.347	0.181	0.263	1.744	-0.836	0.134	-0.239	0.136	0.068	29
Miami, FL PMSA	2,500,625	5	1.075	1.344	1.115	0.347	-0.053	-0.070	0.707	2.306	-0.055	-0.001	-0.042	-0.007	30
Dutchess County, NY PMSA	293,562	2	-0.412	-0.856	-0.990	0.346	0.183	0.247	0.220	0.551	0.183	-0.372	0.141	-0.029	31
Brockton, MA PMSA	268,092	1	-0.251	-0.723	-0.367	0.343	0.097	0.077	2.852	0.236	0.141	-0.355	0.087	0.394	32
Lawrence, MA-NH PMSA	413,626	1	-0.012	-0.072	0.090	0.343	0.107	0.115	1.842	0.236	0.134	-0.273	0.089	0.337	33
New Haven-Meriden, CT PMSA	558,692	1	-0.010	0.095	0.279	0.312	0.180	0.256	-0.576	0.774	0.121	-0.262	0.136	-0.003	34
Stockton-Lodi, CA MSA	674,860	9	0.127	-0.216	0.449	0.266	0.094	0.174	0.150	-0.823	0.100	-0.187	0.062	0.130	35
Boulder-Longmont, CO PMSA	311,786	8	0.021	-0.260	0.157	0.261	-0.004	0.012	4.038	0.684	-0.054	-0.314	-0.007	0.290	36
Medford-Ashland, OR MSA	201,286	9	-0.494	-0.606	-0.438	0.260	-0.168	-0.188	0.917	1.973	0.025	-0.422	-0.138	0.049	37
Riverside-San Bernardino, CA PMSA	4,143,113	9	0.124	-0.489	-0.283	0.256	0.100	0.122	0.644	0.429	0.059	-0.215	0.080	0.104	38
West Palm Beach-Boca Raton, FL MSA	1,279,950	5	0.867	1.034	1.144	0.247	0.014	0.058	0.358	1.695	-0.105	-0.006	0.002	-0.023	39
Atlantic-Cape May, NJ PMSA	367,803	2	-0.148	-0.009	-0.058	0.242	0.068	0.060	0.333	1.751	0.122	-0.231	0.060	0.027	40
Fort Lauderdale, FL PMSA	1,766,476	5	0.913	0.999	1.297	0.222	-0.053	-0.071	0.932	2.262	-0.068	0.050	-0.041	0.019	41
Baltimore, MD PMSA	2,690,886	5	0.238	0.092	0.305	0.215	0.150	0.187	-0.601	-0.347	-0.045	-0.186	0.119	0.065	42
Reno, NV MSA	414,820	8	0.149	0.056	-0.737	0.213	-0.028	-0.138	-0.428	1.308	-0.002	-0.186	0.001	-0.047	43
Hartford, CT MSA	1,231,125	1	-0.684	-0.826	-0.572	0.201	0.097	0.099	0.342	-0.279	0.119	-0.341	0.082	0.048	44

TABLE A5: ALL METROPOLITAN INDICES RANKED BY HOUSING PRICE DIFFERENTIAL, 2005-2010

			Adjusted Differentials					*Raw Differentials*				*Productivity*			
Full Name	Population	Census Division	Land Value	Land Value (All Uses)	Land Value (Un-wtd.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Unavail. Index (z-score)	Const. Price Index	Housing	Tradea-bles	Regulatory Cost Index	Housing Price Rank
Chicago, IL PMSA	8,710,824	3	0.615	1.114	0.407	0.190	0.063	0.069	-0.543	0.532	0.180	0.114	0.053	-0.092	45
Worcester, MA-CT PMSA	547,274	1	-0.194	-0.303	-0.386	0.185	0.101	0.102	2.430	0.236	0.131	-0.181	0.086	0.268	46
Bremerton, WA PMSA	240,862	9	-0.183	-0.245	0.208	0.180	0.046	0.009	0.078	1.107	0.065	-0.231	0.048	0.069	47
Portsmouth-Rochester, NH-ME PMSA	262,128	1	-0.610	-0.501	-0.040	0.179	0.104	0.119	1.035	0.236	-0.028	-0.405	0.085	0.251	48
Portland-Vancouver, OR-WA PMSA	2,230,947	9	0.447	0.408	0.063	0.176	-0.043	-0.062	0.015	0.412	0.033	-0.029	-0.032	-0.014	49
Sarasota-Bradenton, FL MSA	688,126	5	0.424	0.001	0.278	0.163	-0.088	-0.053	1.563	1.822	-0.074	-0.090	-0.082	0.076	50
Manchester, NH PMSA	212,326	1	-0.417	-0.509	-0.287	0.162	0.111	0.146	2.637	0.236	-0.018	-0.332	0.087	0.406	51
Modesto, CA MSA	510,385	9	0.008	-0.260	0.059	0.161	0.048	0.049	-0.156	-0.715	0.100	-0.123	0.041	0.017	52
Fresno, CA MSA	1,063,899	9	-0.100	-0.640	-0.565	0.129	-0.009	-0.024	1.219	-0.783	0.102	-0.132	-0.004	0.173	53
Tacoma, WA PMSA	796,836	9	0.393	0.146	0.034	0.122	0.056	0.037	-0.158	0.371	0.063	0.030	0.052	0.116	54
Portland, ME MSA	256,178	1	-0.422	-0.345	-0.236	0.120	-0.077	-0.025	0.888	0.989	-0.062	-0.325	-0.077	0.179	55
Eugene-Springfield, OR MSA	351,109	9	-0.388	-0.627	-0.866	0.085	-0.166	-0.206	0.202	1.622	0.021	-0.207	-0.132	-0.029	56
Olympia, WA PMSA	250,979	9	0.098	-0.437	-0.160	0.081	0.057	0.040	0.671	0.458	0.052	-0.036	0.052	0.106	57
Philadelphia, PA-NJ PMSA	5,332,822	2	0.249	0.381	0.028	0.074	0.066	0.053	0.689	-0.915	0.158	0.088	0.059	-0.007	58
Grand Junction, CO MSA	146,093	8	-0.108	-0.501	-0.266	0.073	-0.221	-0.383	0.504	0.690	-0.070	-0.176	-0.151	-0.022	59
Newburgh, NY-PA PMSA	444,061	2	-0.296	-1.043	-0.713	0.071	0.183	0.255	-0.479	0.045	0.138	-0.097	0.139	-0.111	60
Yuba City, CA MSA	165,539	9	-0.707	-0.671	-0.963	0.071	-0.006	-0.023	-0.707	-0.734	0.098	-0.248	-0.002	0.057	61
Springfield, MA MSA	609,993	1	-0.321	-0.283	0.034	0.056	-0.031	-0.048	0.108	-0.095	0.072	-0.134	-0.023	0.127	62
Denver, CO PMSA	2,445,781	8	0.119	0.320	-0.227	0.050	-0.004	0.012	1.335	-0.597	-0.021	-0.050	-0.007	0.058	63
Fort Collins-Loveland, CO MSA	298,382	8	-0.344	-0.672	-0.262	0.036	-0.134	-0.226	0.873	0.107	-0.065	-0.216	-0.093	-0.007	64
Merced, CA MSA	245,321	9	-0.144	-0.557	-0.342	0.026	0.062	0.290	0.649	-0.915	0.100	-0.036	0.001	0.090	65
Wilmington-Newark, DE-MD PMSA	635,430	5	0.040	-0.502	-0.199	0.018	0.066	0.054	0.750	-0.697	0.045	-0.003	0.059	0.119	66
Norfolk-Virginia Beach-Newport News, VA- MSA	1,667,410	5	-0.123	-0.417	-0.237	0.006	-0.062	-0.032	-0.167	1.489	-0.104	-0.138	-0.059	0.054	67
Las Vegas, NV-AZ MSA	2,141,893	8	0.869	0.579	0.222	-0.002	0.046	-0.049	-1.453	0.147	0.080	0.320	0.061	-0.122	68
Hagerstown, MD PMSA	145,910	5	-0.315	-0.827	-1.106	-0.003	0.148	0.176	0.188	-0.499	-0.077	-0.196	0.119	0.027	69
Phoenix-Mesa, AZ MSA	4,364,094	8	0.414	-0.082	-0.626	-0.004	-0.002	0.000	1.003	-0.731	-0.104	0.041	-0.002	0.128	70
Fort Myers-Cape Coral, FL MSA	586,908	5	0.183	-0.082	0.583	-0.005	-0.078	-0.070	-0.494	1.168	-0.098	-0.043	-0.068	-0.094	71
Milwaukee-Waukesha, WI PMSA	1,559,667	3	-0.398	-0.695	-0.472	-0.014	-0.021	-0.008	-0.455	0.618	0.066	-0.090	-0.021	0.039	72
Madison, WI MSA	491,357	3	0.105	0.031	-0.340	-0.023	-0.092	-0.171	0.374	-0.858	0.013	0.048	-0.061	0.060	73
Minneapolis-St. Paul, MN-WI MSA	3,269,814	4	0.101	0.102	-0.201	-0.031	0.028	0.000	0.155	-0.475	0.139	0.130	0.030	-0.013	74
Visalia-Tulare-Porterville, CA MSA	429,668	9	-0.327	-0.409	-0.568	-0.032	-0.017	-0.033	0.371	-0.465	0.087	-0.011	-0.011	0.073	75
Tucson, AZ MSA	1,020,200	8	-0.256	-0.534	-0.664	-0.035	-0.126	-0.166	0.250	-0.289	-0.113	-0.153	-0.098	0.122	76
Asheville, NC MSA	251,894	5	-0.460	-0.842	-0.483	-0.047	-0.196	-0.263	0.149	1.863	-0.243	-0.291	-0.151	-0.014	77
Salem, OR PMSA	396,103	9	-0.272	-0.427	-0.308	-0.049	-0.043	-0.063	0.626	0.195	0.026	-0.044	-0.032	0.019	78
Fort Pierce-Port St. Lucie, FL MSA	406,296	5	0.025	-0.215	0.096	-0.053	-0.096	-0.166	0.347	1.739	-0.105	-0.050	-0.066	-0.039	79
Bakersfield, CA MSA	807,407	9	-0.508	-0.640	-1.106	-0.061	0.004	-0.108	-0.316	-0.234	0.077	-0.063	0.029	0.024	80
Fort Walton Beach, FL MSA	178,473	5	-0.152	-0.001	0.463	-0.066	-0.146	-0.213	-0.465	1.435	-0.116	-0.110	-0.109	-0.035	81
Tampa-St. Petersburg-Clearwater, FL MSA	2,747,272	5	0.287	0.074	0.047	-0.076	-0.095	-0.136	0.003	0.611	-0.072	0.096	-0.071	0.016	82
Orlando, FL MSA	2,082,421	5	0.369	-0.077	-0.056	-0.082	-0.087	-0.110	0.131	0.344	-0.071	0.135	-0.069	0.005	83
Kenosha, WI PMSA	165,382	3	-0.215	-0.977	-0.653	-0.100	0.063	0.069	1.863	0.914	0.038	0.028	0.053	0.093	84
Allentown-Bethlehem-Easton, PA MSA	706,374	2	-0.111	-0.813	-0.571	-0.108	-0.015	0.083	0.459	-0.396	0.071	0.092	-0.035	-0.068	85
Richmond-Petersburg, VA MSA	1,119,459	5	-0.508	-0.906	-0.595	-0.114	-0.025	-0.069	-0.796	-0.980	-0.104	-0.139	-0.011	-0.022	86
Charleston-North Charleston, SC MSA	659,191	5	-0.235	-0.066	-0.450	-0.120	-0.094	-0.077	-1.187	1.522	-0.167	-0.098	-0.084	-0.091	87
Melbourne-Titusville-Palm Bay, FL MSA	536,357	5	0.131	-0.534	0.019	-0.135	-0.096	-0.058	0.400	1.707	-0.056	0.105	-0.090	0.001	88
Racine, WI PMSA	200,601	3	-0.723	-1.196	-0.916	-0.149	-0.019	0.022	-1.269	1.215	0.037	-0.060	-0.025	0.040	89

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			Adjusted Differentials						*Raw Differentials*			*Productivity*			
Full Name	Population	Census Division	Land Value	Land Value (All Uses)	Land Value (Un-wtd.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Unavail. Index (z-score)	Const. Price Index	Housing	Tradeables	Regulatory Cost Index	Housing Price Rank
Salt Lake City-Ogden, UT MSA	1,567,650	8	0.091	0.075	0.729	-0.152	-0.105	-0.158	-0.451	2.082	-0.108	0.085	-0.078	0.044	90
Jacksonville, FL MSA	1,301,808	5	0.054	-0.513	-0.045	-0.161	-0.079	-0.118	0.746	0.886	-0.133	0.060	-0.058	0.087	91
Daytona Beach, FL MSA	587,512	5	-0.148	-0.432	-0.018	-0.162	-0.152	-0.181	-0.783	1.526	-0.082	0.039	-0.123	-0.076	92
Gainesville, FL MSA	243,574	5	-0.607	-0.655	-0.607	-0.166	-0.146	-0.157	-0.181	-0.661	-0.108	-0.120	-0.122	-0.054	93
Albuquerque, NM MSA	841,428	8	-0.085	-0.167	-0.169	-0.167	-0.113	-0.185	0.998	-0.843	-0.078	0.067	-0.080	0.033	94
Colorado Springs, CO MSA	604,542	8	-0.226	-0.247	-0.049	-0.188	-0.122	-0.133	0.289	-0.328	-0.048	0.061	-0.102	-0.025	95
Lancaster, PA MSA	507,766	2	-0.489	-0.859	-0.660	-0.199	-0.121	-0.263	0.082	-0.830	-0.036	0.007	-0.070	-0.109	96
Ann Arbor, MI PMSA*	630,518	3	-0.491	-0.855	-1.109	-0.205	-0.003	-0.023	1.273	-0.937	0.026	0.038	0.001	0.078	97
Raleigh-Durham-Chapel Hill, NC MSA	1,589,388	5	-0.222	-0.663	-0.427	-0.208	-0.042	-0.035	1.146	-1.014	-0.210	-0.029	-0.038	0.012	98
Spokane, WA MSA	468,684	9	-0.655	-0.379	-0.436	-0.219	-0.123	-0.128	0.799	-0.083	-0.032	-0.011	-0.103	0.051	99
Myrtle Beach, SC MSA	263,868	5	-0.588	-0.634	-0.576	-0.220	-0.169	-0.097	-0.940	1.590	-0.228	-0.147	-0.159	0.037	100
New Orleans, LA MSA*	1,211,035	7	-0.360	-0.105	-0.307	-0.231	-0.090	-0.167	-2.352	2.222	-0.102	0.029	-0.059	-0.254	101
Albany-Schenectady-Troy, NY MSA	906,208	2	-1.219	-1.195	-1.566	-0.233	-0.035	-0.074	-0.186	-0.277	0.011	-0.114	-0.021	-0.082	102
York, PA MSA	428,937	2	-0.502	-0.920	-0.420	-0.254	-0.055	-0.098	0.879	-0.821	0.001	0.079	-0.038	-0.020	103
Provo-Orem, UT MSA	545,307	8	0.256	0.149	0.449	-0.254	-0.132	-0.168	-0.513	1.480	-0.112	0.244	-0.123	0.054	104
Boise City, ID MSA	571,271	8	-0.327	-0.387	0.126	-0.257	-0.154	-0.192	-1.029	0.354	-0.090	0.060	-0.122	-0.074	105
Nashville, TN MSA	1,495,419	6	-0.333	-0.535	-0.176	-0.264	-0.074	-0.094	-1.066	-0.785	-0.097	0.067	-0.058	-0.007	106
Yuma, AZ MSA	196,972	8	-1.081	-1.239	-1.615	-0.266	-0.134	-0.203	-0.458	-1.078	-0.079	-0.121	-0.098	0.061	107
Greeley, CO PMSA	254,759	8	-0.457	-0.841	-0.744	-0.267	-0.004	0.010	-0.635	-0.919	-0.117	0.020	-0.007	-0.054	108
Savannah, GA MSA	343,092	5	-0.418	-0.958	-0.655	-0.278	-0.101	-0.147	-0.224	1.506	-0.158	0.024	-0.076	0.024	109
Detroit, MI PMSA*	4,373,040	3	-0.332	-0.504	-0.344	-0.285	-0.003	-0.024	-0.253	-0.219	0.040	0.165	0.002	0.031	110
Austin-San Marcos, TX MSA	1,705,075	7	-0.173	-0.515	-0.466	-0.285	-0.042	-0.057	1.075	-1.225	-0.189	0.079	-0.032	0.081	111
Atlanta, GA MSA	5,315,841	5	-0.046	-0.546	-0.373	-0.290	0.007	0.042	0.080	-1.209	-0.080	0.184	-0.002	-0.011	112
Reading, PA MSA	407,125	2	-0.022	-0.344	0.015	-0.295	-0.057	-0.043	0.703	-0.609	0.036	0.308	-0.051	-0.051	113
St. Louis, MO-IL MSA	2,733,694	4	-0.687	-0.954	-0.527	-0.295	-0.058	-0.128	-1.564	-0.870	0.046	0.092	-0.034	-0.081	114
Vineland-Millville-Bridgeton, NJ PMSA	157,745	2	-0.626	-0.922	-0.624	-0.297	0.075	0.098	1.595	0.326	0.120	0.180	0.058	0.031	115
Roanoke, VA MSA	243,506	5	-0.820	-0.915	-0.723	-0.306	-0.113	-0.111	-1.266	0.504	-0.138	-0.061	-0.097	-0.009	116
Billings, MT MSA	144,797	8	-0.585	-0.797	-0.701	-0.316	-0.171	-0.298	-0.556	-0.857	-0.073	0.058	-0.162	-0.119	117
Harrisburg-Lebanon-Carlisle, PA MSA	667,425	2	-0.423	-0.594	-0.585	-0.323	-0.059	-0.015	0.643	-0.243	0.009	0.171	-0.061	-0.034	118
Lakeland-Winter Haven, FL MSA	583,403	5	-0.219	-1.106	-0.707	-0.324	-0.145	-0.197	0.385	0.152	-0.049	0.191	-0.112	-0.016	119
Glens Falls, NY MSA	128,774	2	-2.107	-2.775	-2.776	-0.328	-0.139	-0.142	-2.552	0.574	-0.047	-0.199	-0.118	-0.102	120
Green Bay, WI MSA	247,319	3	-0.658	-0.589	-0.460	-0.328	-0.084	-0.068	-0.419	-0.279	-0.008	0.098	-0.075	-0.012	121
Baton Rouge, LA MSA	685,419	7	-0.605	-0.794	-0.347	-0.344	-0.065	-0.042	-1.511	0.217	-0.129	0.041	-0.061	-0.225	122
Columbus, OH MSA	1,718,303	3	-0.368	-0.792	-0.708	-0.348	-0.046	-0.024	0.216	-1.286	-0.024	0.181	-0.044	-0.146	123
Cleveland-Lorain-Elyria, OH PMSA*	2,192,053	3	-0.306	-0.650	-0.445	-0.349	-0.083	-0.105	-0.704	0.555	0.016	0.228	-0.065	-0.134	124
Cincinnati, OH-KY-IN PMSA	1,776,911	3	-0.309	-0.490	-0.619	-0.350	-0.040	-0.036	-1.026	-0.908	-0.046	0.191	-0.035	-0.120	125
Pensacola, FL MSA	455,102	5	-1.076	-0.895	-1.073	-0.356	-0.193	-0.255	-1.495	1.141	-0.116	-0.045	-0.151	-0.165	126
Appleton-Oshkosh-Neenah, WI MSA	385,264	3	-1.473	-1.824	-1.522	-0.359	-0.092	-0.081	-0.376	-0.538	-0.035	-0.064	-0.081	-0.010	127
Louisville, KY-IN MSA	1,099,588	6	-0.654	-0.798	-0.475	-0.363	-0.114	-0.141	-1.126	-0.792	-0.070	0.094	-0.090	-0.137	128
Fayetteville-Springdale-Rogers, AR MSA	425,685	7	-0.483	-0.775	-0.385	-0.374	-0.130	-0.157	-0.627	-0.005	-0.250	0.012	-0.105	-0.205	129
Richland-Kennewick-Pasco, WA MSA	245,649	9	-0.556	-0.581	-0.553	-0.375	0.026	0.120	0.832	-0.813	-0.016	0.172	0.001	0.081	130
Charlotte-Gastonia-Rock Hill, NC-SC MSA	1,937,309	5	-1.233	-2.105	-1.748	-0.377	-0.056	-0.059	-1.288	-1.180	-0.223	-0.156	-0.047	-0.009	131
Akron, OH PMSA*	699,935	3	-0.709	-1.242	-0.627	-0.379	-0.083	-0.105	-0.026	-1.095	-0.005	0.134	-0.065	-0.087	132
St. Cloud, MN MSA	189,148	4	-0.977	-1.231	-1.125	-0.380	-0.130	-0.268	-0.404	-0.409	0.125	0.172	-0.079	-0.034	133
Des Moines, IA MSA	536,664	4	-1.074	-1.224	-1.103	-0.388	-0.063	-0.006	-1.475	-1.108	-0.090	0.000	-0.066	-0.131	134

TABLE A5: ALL METROPOLITAN INDICES RANKED BY HOUSING PRICE DIFFERENTIAL, 2005-2010

			Adjusted Differentials						*Raw Differentials*			*Productivity*			
Full Name	Population	Census Division	Land Value	Land Value (All Uses)	Land Value (Un-wtd.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Unavail. Index (z-score)	Const. Price Index	Housing	Tradeables	Regulatory Cost Index	Housing Price Rank
Benton Harbor, MI MSA*	160,472	3	-1.438	-1.518	-0.967	-0.398	-0.132	-0.088	-1.088	1.024	-0.035	-0.023	-0.122	-0.009	135
Greensboro--Winston Salem--High Point, NC MSA	1,416,374	5	-0.708	-1.109	-0.614	-0.400	-0.137	-0.185	-0.752	-1.256	-0.221	0.009	-0.105	0.023	136
Champaign-Urbana, IL MSA	195,671	3	-0.517	-0.789	-0.991	-0.403	-0.153	-0.228	-0.836	-1.337	0.067	0.284	-0.113	-0.161	137
Gary, IN PMSA	657,809	3	-0.225	-0.210	-0.098	-0.403	0.063	0.069	-1.399	0.121	0.056	0.337	0.053	-0.056	138
Kansas City, MO-KS MSA	2,005,888	4	-0.718	-0.976	-0.774	-0.411	-0.062	-0.083	-1.382	-1.125	0.045	0.208	-0.048	-0.112	139
Birmingham, AL MSA	997,770	6	-0.907	-1.052	-0.598	-0.412	-0.061	-0.050	-0.417	-0.712	-0.093	0.043	-0.054	-0.037	140
Knoxville, TN MSA	785,490	6	-0.788	-1.069	-0.442	-0.412	-0.143	-0.148	-0.864	0.460	-0.180	0.021	-0.120	-0.021	141
Lansing-East Lansing, MI MSA	453,603	3	-1.273	-1.415	-1.535	-0.414	-0.099	-0.049	-0.553	-1.075	0.009	0.062	-0.096	0.048	142
Hamilton-Middletown, OH PMSA	363,184	3	-0.360	-1.020	-0.089	-0.418	-0.040	-0.037	-0.580	-1.069	-0.067	0.223	-0.035	-0.204	143
La Crosse, WI-MN MSA	132,923	3	-0.576	-0.493	-0.421	-0.418	-0.185	-0.262	-0.406	0.327	-0.014	0.198	-0.140	0.056	144
Dallas, TX PMSA	4,399,895	7	-0.405	-0.556	-0.275	-0.429	-0.001	0.008	-0.666	-0.963	-0.173	0.144	-0.002	-0.094	145
Grand Rapids-Muskegon-Holland, MI MSA	1,157,672	3	-1.174	-1.083	-0.966	-0.435	-0.110	-0.129	-0.463	-0.958	-0.089	0.018	-0.089	-0.017	146
Columbia, SC MSA	627,630	5	-0.907	-0.977	-0.876	-0.436	-0.144	-0.182	-1.110	-0.669	-0.214	-0.005	-0.114	-0.007	147
Hickory-Morganton-Lenoir, NC MSA	365,364	5	-0.878	-1.483	-1.004	-0.437	-0.203	-0.188	-0.915	-0.391	-0.281	-0.052	-0.175	-0.072	148
Lynchburg, VA MSA	232,895	5	-1.155	-1.399	-0.891	-0.441	-0.170	-0.197	-0.919	-0.325	-0.131	-0.006	-0.139	-0.002	149
Chattanooga, TN-GA MSA	510,388	6	-0.500	-0.612	-0.628	-0.446	-0.149	-0.218	-1.326	-0.156	-0.137	0.178	-0.111	-0.027	150
Huntsville, AL MSA	406,316	6	-0.324	-0.809	-0.335	-0.446	-0.085	-0.186	-2.306	-0.228	-0.133	0.225	-0.049	-0.039	151
State College, PA MSA	146,212	2	-1.283	-1.550	-1.504	-0.447	-0.191	-0.219	1.122	-0.808	-0.030	0.040	-0.156	-0.007	152
Mobile, AL MSA	591,599	6	-1.192	-1.409	-1.200	-0.457	-0.173	-0.269	-2.682	0.013	-0.133	0.002	-0.126	-0.085	153
Lincoln, NE MSA	281,531	4	-0.496	-0.755	-0.706	-0.461	-0.200	-0.172	0.793	-1.330	-0.095	0.225	-0.176	0.052	154
Janesville-Beloit, WI MSA	160,155	3	-0.418	-0.808	-0.615	-0.467	-0.114	-0.128	-0.703	-1.175	0.003	0.321	-0.093	-0.003	155
Bryan-College Station, TX MSA	179,992	7	-1.240	-1.519	-1.346	-0.478	-0.262	-0.522	0.363	-1.096	-0.175	-0.003	-0.165	0.013	156
Little Rock-North Little Rock, AR MSA	657,416	7	-0.866	-0.988	-0.530	-0.480	-0.124	-0.144	-1.819	-0.743	-0.136	0.105	-0.101	-0.240	157
Indianapolis, IN MSA	1,823,690	3	-0.574	-0.992	-0.635	-0.483	-0.073	-0.107	-1.730	-1.337	-0.044	0.245	-0.054	-0.100	158
Greenville-Spartanburg-Anderson, SC MSA	1,096,009	5	-1.021	-1.397	-0.854	-0.485	-0.124	-0.152	-1.574	-0.784	-0.231	-0.002	-0.099	-0.062	159
Dayton-Springfield, OH MSA*	933,312	3	-0.737	-0.940	-0.506	-0.485	-0.127	-0.162	-1.482	-1.357	-0.069	0.198	-0.100	-0.220	160
Duluth-Superior, MN-WI MSA*	242,041	4	-0.820	-1.200	-1.324	-0.485	-0.184	-0.399	-0.860	0.261	0.077	0.280	-0.108	-0.061	161
Lexington, KY MSA	554,107	6	-0.441	-0.482	-0.180	-0.490	-0.116	-0.051	-0.098	-1.121	-0.098	0.255	-0.113	-0.038	162
Toledo, OH MSA*	631,275	3	-1.465	-1.721	-1.434	-0.493	-0.113	-0.192	-2.216	-0.488	0.011	0.104	-0.078	-0.203	163
Cedar Rapids, IA MSA	209,226	4	-1.111	-1.310	-0.924	-0.500	-0.112	-0.093	-1.365	-1.236	-0.067	0.111	-0.100	-0.083	164
Kalamazoo-Battle Creek, MI MSA	462,250	3	-1.334	-1.475	-1.178	-0.502	-0.118	-0.136	-0.929	-0.929	-0.029	0.104	-0.097	0.033	165
Houston, TX PMSA	5,219,317	7	-0.305	-0.523	-0.579	-0.503	0.025	0.044	-0.070	-1.000	-0.142	0.272	0.017	-0.071	166
Wausau, WI MSA	131,612	3	-1.368	-1.787	-1.441	-0.504	-0.121	-0.150	-0.669	-0.833	-0.038	0.092	-0.097	-0.015	167
Canton-Massillon, OH MSA*	408,005	3	-0.874	-1.186	-0.855	-0.510	-0.116	-0.031	-1.105	-0.798	-0.044	0.196	-0.118	-0.175	168
Omaha, NE-IA MSA	799,130	4	-0.683	-0.736	-0.617	-0.512	-0.102	-0.051	-0.433	-1.245	-0.076	0.228	-0.098	-0.033	169
Waterloo-Cedar Falls, IA MSA*	129,276	4	-0.920	-0.946	-0.556	-0.514	-0.306	-0.821	-1.470	-1.256	-0.186	0.091	-0.144	-0.120	170
Pittsburgh, PA MSA*	2,287,106	2	-0.809	-0.941	-1.124	-0.516	-0.098	-0.102	-0.077	0.048	0.029	0.279	-0.083	-0.063	171
Peoria-Pekin, IL MSA*	357,144	3	-1.519	-1.816	-1.708	-0.519	-0.075	-0.101	-0.528	-1.166	0.065	0.168	-0.058	-0.073	172
Biloxi-Gulfport-Pascagoula, MS MSA	355,075	6	-0.870	-1.109	-0.962	-0.526	-0.145	-0.159	-1.131	1.116	-0.156	0.124	-0.120	-0.099	173
Rockford, IL MSA	409,058	3	-0.812	-1.557	-1.440	-0.526	-0.059	-0.002	-1.038	-1.301	0.124	0.360	-0.063	-0.188	174
Augusta-Aiken, GA-SC MSA	516,357	5	-1.136	-1.257	-0.832	-0.528	-0.066	0.031	-1.614	-0.902	-0.136	0.091	-0.078	-0.069	175
Sioux Falls, SD MSA	224,266	4	-0.445	-0.710	-0.628	-0.529	-0.122	-0.194	-1.415	-1.244	-0.167	0.252	-0.134	-0.004	176
Scranton--Wilkes-Barre--Hazleton, PA MSA*	614,565	2	-1.039	-1.473	-1.272	-0.529	-0.165	-0.206	-0.436	-0.012	0.013	0.210	-0.131	-0.087	177
Memphis, TN-AR-MS MSA	1,230,253	6	-0.921	-1.180	-0.443	-0.529	-0.048	-0.071	1.525	-0.817	-0.126	0.147	-0.036	0.109	178
Davenport-Moline-Rock Island, IA-IL MSA*	362,790	4	-1.180	-1.377	-1.275	-0.531	-0.088	0.022	-1.818	-1.185	-0.006	0.183	-0.100	-0.116	179

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			Adjusted Differentials						*Raw Differentials*			*Productivity*			
Full Name	Population	Census Division	Land Value	Land Value (All Uses)	Land Value (Un-wtd.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Unavail. Index (z-score)	Const. Price Index	Housing	Tradeables	Regulatory Cost Index	Housing Price Rank
Galveston-Texas City, TX PMSA	286,814	7	-0.706	-0.738	-0.176	-0.531	0.022	0.046	0.398	2.232	-0.120	0.212	0.013	-0.042	180
Rochester, NY MSA	1,093,434	2	-1.425	-1.452	-2.287	-0.533	-0.079	-0.051	-0.554	0.069	0.029	0.174	-0.073	-0.020	181
Fort Worth-Arlington, TX PMSA	2,113,278	7	-0.598	-0.759	-0.487	-0.535	-0.001	0.008	-0.420	-1.169	-0.153	0.219	-0.002	-0.094	182
Jackson, MS MSA	483,852	6	-1.024	-1.276	-1.297	-0.540	-0.115	-0.126	-2.260	-0.858	-0.131	0.134	-0.096	-0.132	183
Montgomery, AL MSA	354,108	6	-1.247	-1.347	-1.102	-0.542	-0.142	-0.150	-1.685	-0.886	-0.182	0.043	-0.119	-0.047	184
Tulsa, OK MSA	873,304	7	-0.763	-0.877	-1.117	-0.547	-0.105	-0.051	-1.664	-1.102	-0.201	0.171	-0.101	-0.154	185
Bloomington-Normal, IL MSA	167,699	3	-0.800	-0.947	-1.017	-0.550	-0.050	0.093	-0.586	-1.339	0.051	0.320	-0.075	-0.136	186
Oklahoma City, OK MSA	1,213,704	7	-1.027	-1.238	-1.160	-0.555	-0.173	-0.275	-1.067	-1.288	-0.157	0.130	-0.125	-0.074	187
Lafayette, IN MSA	202,331	3	-0.701	-1.185	-0.747	-0.557	-0.171	-0.204	-0.951	-0.146	-0.069	0.274	-0.138	-0.002	188
Tyler, TX MSA	204,665	7	-1.172	-1.532	-1.329	-0.558	-0.156	-0.226	-0.062	-0.918	-0.183	0.065	-0.117	0.113	189
Springfield, MO MSA	383,637	4	-0.859	-1.047	-1.097	-0.567	-0.225	-0.275	-1.324	-1.086	-0.077	0.245	-0.180	-0.029	190
Johnson City-Kingsport-Bristol, TN-VA MSA	503,010	6	-0.900	-1.248	-0.764	-0.567	-0.207	-0.267	-1.498	1.272	-0.197	0.144	-0.163	-0.024	191
Brazoria, TX PMSA	309,208	7	-1.018	-1.529	-1.020	-0.567	0.032	0.057	-0.808	-1.000	-0.135	0.160	0.021	-0.125	192
Buffalo-Niagara Falls, NY MSA*	1,123,804	2	-0.994	-0.949	-0.978	-0.576	-0.076	-0.066	-1.147	-0.484	0.053	0.308	-0.066	-0.088	193
Sumter, SC MSA	104,495	5	-1.239	-1.752	-1.207	-0.576	-0.325	-0.629	-1.557	-0.298	-0.214	0.057	-0.207	-0.017	194
Elkhart-Goshen, IN MSA	200,502	3	-1.159	-1.558	-1.020	-0.581	-0.098	-0.079	-1.460	-1.086	-0.059	0.202	-0.124	-0.140	195
Flint, MI PMSA*	424,043	3	-1.032	-1.440	-1.031	-0.588	-0.003	-0.024	-0.469	-0.943	0.011	0.276	0.002	0.051	196
Amarillo, TX MSA	238,299	7	-0.959	-1.212	-0.999	-0.588	-0.204	-0.282	-0.847	-1.237	-0.160	0.176	-0.156	-0.126	197
Saginaw-Bay City-Midland, MI MSA*	390,032	3	-2.051	-2.375	-1.983	-0.590	-0.118	-0.142	-0.181	-0.613	-0.014	0.103	-0.095	-0.033	198
Erie, PA MSA*	280,291	2	-1.416	-1.364	-1.446	-0.596	-0.187	-0.257	-0.916	1.063	-0.021	0.196	-0.143	-0.054	199
Fayetteville, NC MSA	315,207	5	-0.961	-1.057	-0.479	-0.599	-0.183	-0.225	-1.559	-0.655	-0.208	0.148	-0.146	-0.192	200
San Antonio, TX MSA	1,928,154	7	-0.852	-0.965	-0.759	-0.601	-0.121	-0.119	1.739	-1.254	-0.168	0.205	-0.103	0.060	201
South Bend, IN MSA	267,613	3	-0.676	-1.119	-0.748	-0.602	-0.112	0.001	-2.027	-0.896	-0.059	0.332	-0.121	-0.082	202
Syracuse, NY MSA*	725,610	2	-1.189	-1.331	-1.921	-0.610	-0.096	-0.102	-1.709	-0.542	0.004	0.265	-0.080	-0.163	203
Evansville-Henderson, IN-KY MSA	305,455	3	-1.496	-1.485	-1.230	-0.620	-0.159	-0.338	-1.316	-0.987	-0.052	0.171	-0.095	-0.043	204
Macon, GA MSA	356,873	5	-1.264	-1.566	-1.011	-0.626	-0.071	-0.021	-1.660	-1.024	-0.150	0.160	-0.072	-0.123	205
Rocky Mount, NC MSA	146,596	5	-0.759	-1.029	-0.587	-0.632	-0.163	-0.273	-0.857	-0.513	-0.290	0.165	-0.114	-0.144	206
Lafayette, LA MSA	415,592	7	-1.286	-1.442	-1.224	-0.643	-0.131	-0.154	-1.729	-1.310	-0.169	0.141	-0.106	-0.185	207
Lake Charles, LA MSA	187,554	7	-0.888	-0.859	-0.740	-0.646	-0.107	-0.099	-1.928	0.964	-0.142	0.244	-0.093	-0.243	208
Lubbock, TX MSA	270,550	7	-1.386	-1.720	-1.182	-0.646	-0.209	-0.239	-1.539	-1.385	-0.187	0.113	-0.171	-0.028	209
Wichita, KS MSA	589,195	4	-1.101	-1.304	-1.001	-0.648	-0.135	-0.185	-1.911	-1.327	-0.155	0.206	-0.104	-0.082	210
Fort Wayne, IN MSA	528,408	3	-1.255	-1.590	-1.416	-0.655	-0.141	-0.147	-1.540	-1.283	-0.084	0.246	-0.118	-0.098	211
St. Joseph, MO MSA*	106,908	4	-1.713	-1.808	-1.517	-0.657	-0.205	-0.354	-2.414	-1.104	-0.028	0.199	-0.174	-0.113	212
Utica-Rome, NY MSA*	293,280	2	-1.950	-2.347	-2.233	-0.664	-0.155	-0.322	-1.425	-0.549	-0.026	0.172	-0.094	-0.042	213
Sherman-Denison, TX MSA	120,030	7	-1.606	-2.370	-1.933	-0.670	-	-	-1.646	-1.076	-0.222	0.068	-	-0.107	214
Corpus Christi, TX MSA	391,269	7	-1.196	-1.266	-1.024	-0.674	-0.168	-0.230	-1.155	0.435	-0.209	0.165	-0.129	-0.176	215
Dothan, AL MSA	148,232	6	-1.296	-1.825	-1.451	-0.677	-0.131	-0.001	-1.610	-0.965	-0.217	0.148	-0.140	-0.012	216
Fargo-Moorhead, ND-MN MSA	200,102	4	-0.652	-0.846	-0.869	-0.679	-0.211	-0.456	-2.080	-1.264	-0.097	0.376	-0.125	-0.065	217
Youngstown-Warren, OH MSA*	554,614	3	-1.782	-2.155	-1.652	-0.709	-0.178	-0.208	-0.780	-0.898	-0.020	0.252	-0.145	-0.141	218
Columbus, GA-AL MSA	285,800	5	-0.479	-0.649	-0.481	-0.716	-0.162	-0.175	-1.452	-1.109	-0.151	0.425	-0.135	-0.100	219
El Paso, TX MSA	751,296	7	-0.586	-0.495	-0.086	-0.738	-0.200	-0.133	0.398	-1.159	-0.213	0.377	-0.185	-0.042	220
Killeen-Temple, TX MSA	358,316	7	-1.382	-1.573	-1.133	-0.741	-0.188	-0.214	-1.838	-1.246	-0.239	0.162	-0.155	-0.070	221
Beaumont-Port Arthur, TX MSA*	378,477	7	-1.311	-1.443	-1.389	-0.747	-0.073	-0.104	-1.422	-0.493	-0.155	0.262	-0.055	-0.101	222
Binghamton, NY MSA*	244,694	2	-1.358	-1.592	-1.566	-0.754	-0.127	-0.134	-1.423	0.257	-0.015	0.342	-0.106	-0.122	223
Longview-Marshall, TX MSA	222,489	7	-1.896	-2.429	-2.098	-0.764	-0.201	-0.412	-2.430	-0.891	-0.266	0.081	-0.123	-0.169	224

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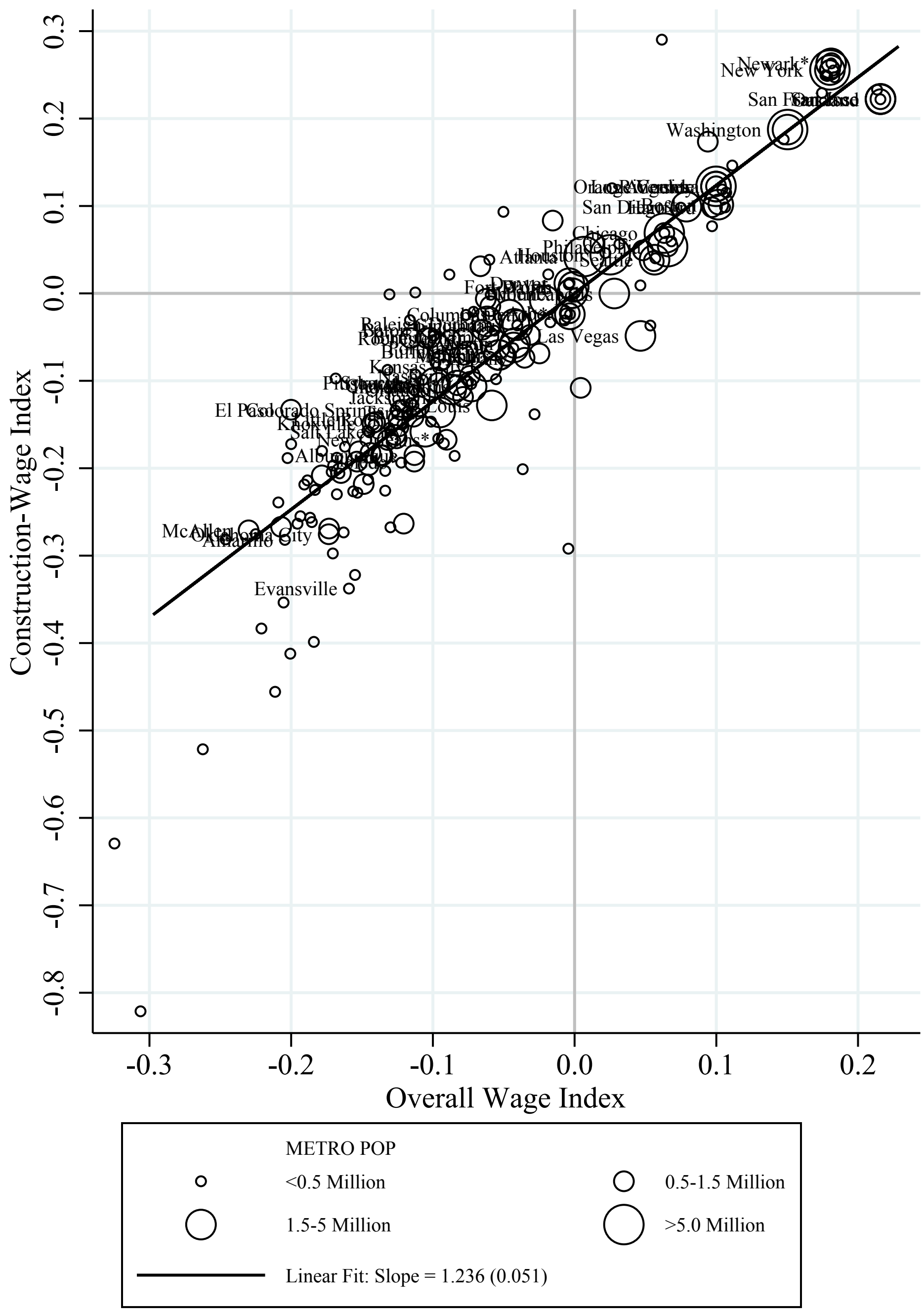
Full Name	Population	Census Division	Land Value	Land Value (All Uses)	Land Value (Un-wtd.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Unavail. Index (z-score)	Const. Price Index	Housing	Tradeables	Regulatory Cost Index	Housing Price Rank
Fort Smith, AR-OK MSA	225,132	7	-1.633	-1.969	-1.691	-0.784	-0.178	-0.180	-1.764	-0.449	-0.187	0.200	-0.179	-0.163	225
Bismarck, ND MSA	106,286	4	-0.925	-1.267	-1.228	-0.837	-	-	-0.446	-1.123	-0.149	0.435	-	-0.075	226
Sioux City, IA-NE MSA*	123,482	4	-1.768	-1.755	-1.885	-0.840	-0.060	0.038	-1.863	-1.259	-0.120	0.288	-0.169	-0.080	227
Jamestown, NY MSA*	133,503	2	-2.423	-2.738	-2.358	-0.931	-0.241	-0.339	-0.790	0.036	-0.013	0.406	-0.183	-0.110	228
Brownsville-Harlingen-San Benito, TX MSA	396,371	7	-1.130	-1.171	-0.349	-0.982	-0.246	-0.281	-0.749	-0.069	-0.240	0.471	-0.201	-0.108	229
McAllen-Edinburg-Mission, TX MSA	741,152	7	-0.497	-0.735	-0.367	-0.990	-0.230	-0.271	-0.733	-1.362	-0.240	0.645	-0.186	-0.118	230
<u>*Census Divisions:*</u>															
New England	9,276,332	1	0.150	0.216	0.270	0.429	0.101	0.114	0.988	0.235	0.130	-0.302	0.083	0.175	4
Middle Atlantic	36,776,228	2	0.439	0.767	0.593	0.288	0.083	0.121	0.201	0.075	0.155	-0.002	0.063	-0.013	2
East North Central	34,629,706	3	-0.336	-0.415	-0.447	-0.234	-0.031	-0.038	-0.628	-0.301	0.043	0.147	-0.025	-0.068	6
West North Central	12,493,078	4	-0.570	-0.732	-0.644	-0.332	-0.064	-0.101	-0.943	-0.892	0.026	0.160	-0.048	-0.062	7
South Atlantic	44,239,778	5	0.090	-0.100	-0.040	-0.049	-0.027	-0.027	-0.006	0.105	-0.102	0.005	-0.023	0.005	5
East South Central	9,515,207	6	-0.746	-0.961	-0.578	-0.437	-0.108	-0.129	-0.882	-0.423	-0.124	0.104	-0.087	-0.033	9
West South Central	26,109,488	7	-0.616	-0.784	-0.613	-0.520	-0.064	-0.072	-0.467	-0.785	-0.167	0.193	-0.053	-0.085	8
Mountain	15,869,775	8	0.196	-0.006	-0.201	-0.043	-0.043	-0.075	0.335	-0.060	-0.059	0.044	-0.030	0.043	3
Pacific	41,103,383	9	0.795	0.910	0.849	0.652	0.090	0.095	0.713	0.980	0.091	-0.312	0.075	0.099	1
<u>*Metropolitan Population:*</u>															
Less than 500,000	31,264,023		-0.661	-0.870	-0.666	-0.228	-0.069	-0.092	-0.359	-0.055	-0.042	-0.006	-0.055	-0.014	4
500,000 to 1,500,000	55,777,644		-0.428	-0.614	-0.398	-0.193	-0.051	-0.058	-0.288	-0.158	-0.045	0.020	-0.042	-0.020	3
1,500,000 to 5,000,000	89,173,333		0.199	0.080	0.097	0.097	0.019	0.017	0.151	0.142	0.008	-0.034	0.016	0.020	2
5,000,000+	49,824,250		0.866	1.321	0.899	0.363	0.093	0.122	0.223	0.011	0.094	0.012	0.073	0.005	1

See Table 1 and text for explanatory details.

Figure A: Construction Wages vs. Overall Wages



Note: Wages are estimated at the CMSA level, but the figure plots PMSAs to be consistent with the other figures. Concentric circles represent multiple PMSAs of different populations in the same CMSA.

Figure B: Construction Prices vs. Construction Wages

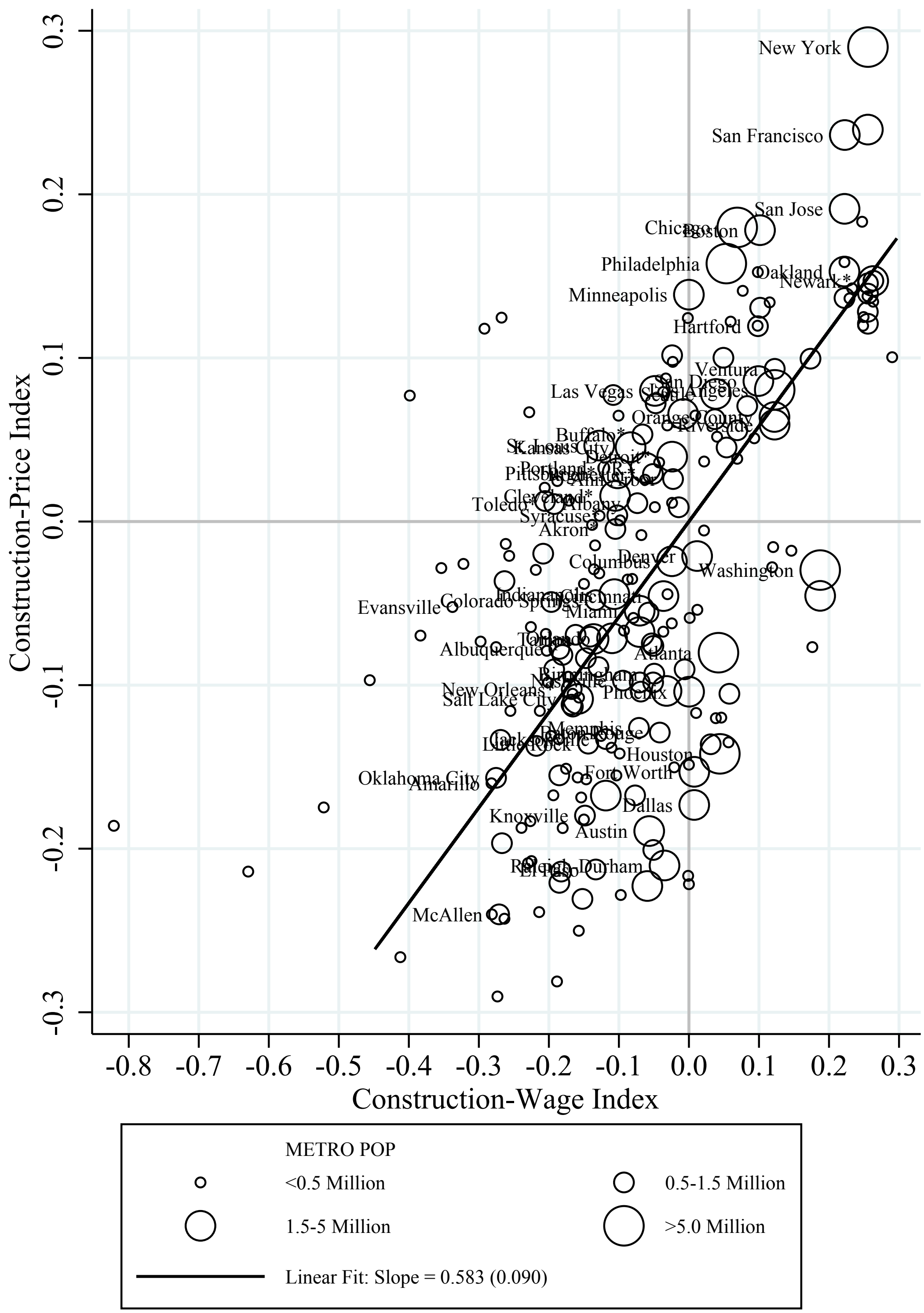


Figure C: Residential vs. All-Use Land Values