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METROPOLITAN LAND VALUES AND HOUSING PRODUCTIVITY

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ABSTRACT

We present the first cross-sectional index of directly-measured land values by metropolitan area, which we use to estimate a housing cost function. This specification incorporates non-land input prices, fits the data well, and passes several econometric tests, validating our design and data. It indicates lands national average cost share is one-third, and the elasticity-of-substitution between inputs is one-half. Greater geographic and regulatory constraints predict housing prices substantially higher than predicted by input prices, supporting the prediction that constraints reduce production efficiency. Estimated housing productivity falls with city population and density. The efficiency costs of typical land-use regulations appear to outweigh associated quality-of-life benefits.

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1 Introduction

Housing accounts for approximately 15 percent of personal consumption expenditures and 44 percent of private fixed assets in the U.S. economy (Bureau of Economic Analysis 2013a and 2013b). Housing values vary widely over space, and this variance is attributed primarily to differences in land values (Case 2007; Davis and Palumbo 2008). Furthermore, recent fluctuations in housing prices may stem primarily from much larger fluctuations in underlying land values (Davis and Palumbo 2008; Nichols et al. 2013). Economists since Ricardo (1817) and George (1881) have sought to quantify the share of property values attributable to land, while land-use policies are a prominent issues facing most local governments today.[1]

Unfortunately, market data on land values have been notoriously piecemeal, and economists have done fairly little to tie such data to actual housing values. In this paper, we estimate an intuitive but previously untested model for housing and land values from the popular Roback (1982) system of urban areas. The model predicts that housing should be more expensive in areas with i) higher land values; ii) higher costs of construction inputs such as materials and labor; and iii) less efficient housing production. We posit and test the prediction that housing production is less efficient in areas with more severe topographical constraints or land-use regulations — sometimes characterized as "regulatory taxes" — which may lower the value of land, even if they raise the value of housing. Consequently, land values disentangle how demand-side factors, such as local quality of life and employment opportunities, pull up the price of housing, from how supply-side factors, such as building inputs and regulatory barriers, push up the price. Our framework permits us to examine whether land-use regulations provide local quality-of-life benefits to compensate residents for their housing costs.

As part of the analysis, we provide the first inter-metropolitan index of directly-observed land values that is cross-sectionally comparable across U.S. metropolitan areas. Theory suggests this index captures the full private value of amenities, employment, and building opportunities combined across metro areas. In relative terms, land values should vary far more across metros than housing values. By using inter-metropolitan data on non-land, as well as land, input prices, we are able both to estimate and test a national cost function for housing services. This model intuitively identifies both distribution and substitution

[1] Summers (2014) argues 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 that cause the real estate of the rich in major metropolitan areas to keep rising in value."

parameters through duality methods (Fuss and McFadden 1978).

Our empirical analysis provides evidence supporting a Constant Elasticity of Substitution (CES) cost model. It passes several specification tests that validate the consistency of our data. With only four measures, the model explains over 85 percent of housing-price variation across metros. The housing-to-land price gradient implies that land acounts for one-third of housing costs, on average. Curvature in the gradient suggests that the cost shares rises from 15 to 50 percent in high-value areas, implying an elasticity of substitution between land and other inputs of about 0.5.

Housing price deviations from the cost surface predicted by input prices provide a new measure of local productivity (or efficiency) in the housing sector. This metric is a summary indicator of how efficiently local producers transform inputs into valued housing services. This measure complements productivity indices for tradeable sectors — seen in Beeson and Eberts (1989), Shapiro (2006), and Albouy (Forthcoming) — and indices for local quality of life — as in Roback (1982), Gyourko and Tracy (1991), and others. As predicted, regulatory and geographic constraints — as measured by by Gyourko, Saiz, and Summers (2008) and Saiz (2010) — reduce housing productivity. A standard deviation increase in aggregate measures of these constraints is associated with 8 to 9 percent higher costs. Among disaggregate regulation measures, state political and court involvement approval, and local political pressure and project predict the highest efficiency costs.

Housing productivity differences across metro areas are large, with a standard deviation equal to 22 percent of total costs. Observed regulations explain 39 percent of this variance. Contrary to common assumptions (e.g. Rappaport 2007) that metro-level productivity levels in tradeables and housing are equal, we find the two are negatively correlated across areas. For example, the San Francisco Bay Area is very efficient in producing tradeable output, but very *in*efficient in producing housing. In general, housing productivity falls with city size, suggesting there are urban diseconomies of scale in housing production. Additionally, housing inefficiency from land-use regulation is correlated with higher quality of life, but at such low magnitudes that the typical regulation is welfare-reducing, even if causality is assumed to run entirely from regulation to quality of life.

2 Previous Literature on Land and Housing Costs

Our transaction-based measure differs from common 'residual' measures of land values, derived from the difference between a property's entire value and the estimated value of its structure. Davis and Palumbo (2008) use this method to estimate land values across metro areas and over time, finding that the cost share of land in housing values rose to 51 percent in 2004. Using a similar method, Case (2007) calculates lower cost shares of land of 29 percent in 2000 and 38 percent in 2005.[2]

As Davis and Heathcote (2007) note, the residual method attaches "the label 'land' to anything that makes a house worth more than the cost of putting up a new structure of similar size and quality on a vacant lot." As we emphasize here, the residual method will attribute higher costs stemming from inefficiencies in factor usage – possibly from geographic and regulatory constraints – to higher land values.[3] Such inefficiencies do not raise the market value of land for purchasers. The residual method can also cause researchers to find negative land values — as Davis and Heathcote (2007) find for residential housing in 1940, and Case (2007) finds for commercial real estate in 1992.

We estimate the cost function of housing using metro-level variation in construction costs, regulatory and geographic constraints, and transaction-based measures of land values. None have taken the full approach attempted here, although Rosen (1978), Polinsky and Ellwood (1979), and Arnott and Lewis (1979) are relevant predecessors. McDonald (1981) surveys these and other early estimates, and find that in most estimtes of the elasticity of substitution between land and materials to be loosely centered around 0.5, pointing out that measurement error may bias these estimates downwards. Our approach, focused on prices, pooled at the city level, is largely immune to this problem. [4] Thorsnes (1997) is unique among our predecessors in having market transactions for land. His sample is limited to 219 properties in Portland, and has no variation in non-land costs, or in regulatory or geographic constraints. Our much larger sample and richer sample taken across the United

[2]Davis and Palumbo (2008) note that they use "several formulas, different sources of data, and a few assumptions about unobserved quantities, none of which is likely to be exactly right." Using numbers from much earlier, Muth's (1969) suggests numbers closer to 10 to 15 percent, with possibly as little as 5 percent due to unimproved land.

[3]Hedonic methods can also provide estimates of land values from housing values. Using an augmented residual method based on hedonics, Glaeser and Ward (2009) estimate a value of $16,000 per acre of land in the Greater Boston area, while presenting evidence that the market price of an acre is approximately $300,000 if new housing can be built on it. They attribute this discrepancy to zoning regulations.

[4]Epple et al. (2010) use an alternative estimator based on separately assessed (not transacted) land and structure values for houses in Alleghany County, PA, and estimate an elasticity of substitution greater than one. Ahlfeldt and McMillen (2014) obtain similar estimates for Berlin and Chicago. One caveat to these findings is that they are based on a reverse regression of log land values on property values. Any kind of 'optimization errors' due to housing capital and land being combined in suboptimal proportions creates a bias similar to measurement error in the reverse regression. This imparts an upward bias to the elasticity of substitution estimated using the Epple et al. approach. Thus, 'classic' and 'reverse' regression estimates may bracket the correct elasticity.

States allows us to consider and test a deeper model.[5]

A few studies have examined more limited housing and land value data using less formal methods. Rose (1992) examines 27 cities in Japan and finds that fewer geographic constraints correlate with both lower land and lower housing values. 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. Glaeser and Gyourko (2003) use an enhanced residual method to infer land values, and find that housing and land values differ most in heavily regulated environments. Glaeser, Gyourko, and Saks (2005b) 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 the benefits they consider, mainly from preserving views.

Three recent papers make use of the source we use for land data, the CoStar COMPS data, for analyses within metro areas. Haughwout, Orr, and Bedoll (2008) construct a land price index for 1999 to 2006 within the New York metro area, demonstrating the land data's extensive coverage. Kok, Monkkonnen, and Quigley (2014) document land sales within the San Francisco Bay Area, and relate the sales prices to the topographical, demographic, and regulatory features of the site. Neither connects land values to housing prices. Nichols, Oliner, and Mulhall (2013) construct a panel of land-value indices for 23 metro areas from the 1990s through 2009. Their index is comparable only within metros over time, not cross-sectionally across space. They demonstrate that land values vary more than housing values across time, as our analysis demonstrates across space.

3 Model of Land Values and Housing Production

Our econometric model uses a housing cost function for housing embedded within a general-equilibrium model of urban areas, similar to one proposed, but not pursued, by Roback (1982).[6] Albouy (Forthcoming) develops predictioins relating housing prices to land and local productivity, but lacks the data to test them.[7] The national economy contains many

[5]Thorsnes (1997) and Sirmans, Kau, and Lee (1979) estimate a variable elasticity of substitution using small samples drawn from a handful of cities. Sirmans et al. reject the hypothesis of a constant elasticity of substitution, but Thorsnes finds that, "... the CES is the appropriate functional form."

[6]Although Roback (1982) first proposed such a model, she did not develop or test its predictions. The most she says is 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."

[7]van Nieuwerburgh and Weill (2010) embed a Roback-style model in a dynamic framework, which they use to study, among other issues, the effects of land-use restrictions on price dispersion across metropoli-

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. Cities differ in their productivity in the housing sector, A_j^Y.

3.1 Cost Function for Housing

Firsm produce housing, Y_j, with land L and materials M according to the function

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

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. Land earns a city-specific price, r_j, while materials earn price v_j. We operationalize M as the installed structure component of housing, so v_j represents an index of construction input prices, e.g. an aggregate of local labor and mobile capital. Unit costs in the housing sector, equal to marginal and average costs, are $c^Y(r_j, v_j; A_j^Y) \equiv \min_{L,M}\{r_j L + v_j M : F^Y(L, M; A_j^Y) = 1\}$.[8]

We assume the housing market in city j is perfectly competitive.[9] Then, in cities with postive production, equilibrium housing prices will equal the unit cost:

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

tan areas. Their model emphasizes (we believe rightly) that changing marginal valuations for locations are needed, in addition to regulations, to explain rising housing-price dispersion. Nevertheless, their framework has an inflexible production technology without land, and disallows income effects in housing demand.

[8]The use of a single function to model the production of a heterogenous housing stock is well established in the literature, beginning with Muth (1960) and Olsen (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.

[9]Although this assumption may seem stringent, the empirical evidence is consistent with perfect competition in the construction sector. 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 the construction industry having no market power. This seems sensible as new homes must compete with the stock of existing homes. If markets are imperfectly competitive, then A_j^Y will vary inversely with the mark-up on housing prices above marginal costs.

Figure 1A illustrates how we estimate housing productivity, holding v_j constant. The thick solid curve represents the cost function for cities with average productivity. 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.

We adopt a hat notation where $\hat{z}^j$ represents, for any variable z, city j's log deviation from the national average, $\bar{z}$, i.e. $\hat{z}^j = \ln z^j - \ln \bar{z}$. A first-order log-linear approximation of equation (2) expresses how housing prices vary with input prices and productivity: $\hat{p}_j = \phi^L \hat{r}_j + (1 - \phi^L)\hat{v}_j - \hat{A}_j^Y$. ϕ^L is the cost share of land at the average, and A_j^Y is normalized so that a one-point increase in $\hat{A}_j^Y$ corresponds to a one-point reduction in log costs.[10] Rearranged, housing productivity can be be imputed from the difference between a weighted average of input costs and housing prices:

$$\hat{A}_j^Y = \phi^L \hat{r}_j + (1 - \phi^L)\hat{v}_j - \hat{p}_j. \tag{3}$$

If housing productivity is factor neutral, i.e., $F^Y(L, M; A_j^Y) = A_j^Y F^Y(L, M; 1)$, then the second-order log-linear approximation of (2), drawn in figure 1B, is

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

where σ^Y is the elasticity of substitution between land and non-land inputs. The elasticity of substitution is less than one if costs increase in the square of the factor-price difference, $(\hat{r}_j - \hat{v}_j)^2$. The cost share of land in a particular city is given approximately by

$$\phi_j^L = \phi^L + \phi^L(1 - \phi^L)(1 - \sigma^Y)(\hat{r}_j - \hat{v}_j), \tag{5}$$

and thus is increasing with $\hat{r}_j - \hat{v}_j$ when $\sigma^Y < 1$.

Our estimates of $\hat{A}_j^Y$ assume that a single elasticity of substitution describes production in all cities. If this elasticity varies, then our 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. When production has low substitutability, the cost curve is flatter, as producers are less able to substitute away

[10]This normalization implies that at the national average productivity level and prices, $\bar{A}^Y = -\bar{p}/[\partial c^Y(\bar{r}, \bar{v}, \bar{A}^Y)/\partial A]$.

from land in higher-value cities. This has the same net observable consequence on housing prices, although the concepts may have different implications for quantities.[11]

Appendix B shows that modeling non-neutral productivity requires adding another term to equation 4 to account for the productivity of land relative to materials, A_j^{YL}/A_j^{YM}:

$$-\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j-\hat{v}_j)(\hat{A}_j^{YL}-\hat{A}_j^{YM}). \tag{6}$$

If $\sigma^Y < 1$, then cities where land is expensive relative to materials, i.e., $\hat{r}_j > \hat{v}_j$, see greater cost reductions where the relative productivity level, A_j^{YL}/A_j^{YM}, is higher.

3.2 Adapting a Translog Econometric Cost Function

We estimate housing prices using a translog cost function (Christensen et al. 1973) with land and non-land factor prices, and Z^j, a vector of city-level attributes:

$$\hat{p}_j = \beta_1\hat{r}_j + \beta_2\hat{v}_j + \beta_3(\hat{r}_j)^2 + \beta_4(\hat{v}_j)^2 + \beta_5(\hat{r}_j\hat{v}_j) + Z^j\gamma + \varepsilon_j, \tag{7}$$

This specification is equivalent to the second-order approximation of the cost function (see, e.g., Binswager 1974, and Fuss and McFadden 1978) under the CRS restrictions

$$\beta_1 = 1-\beta_2, \beta_3 = \beta_4 = -\beta_5/2, \tag{8}$$

where $\phi^L = \beta_1$ and, with factor-neutral productivity, $\sigma^Y = 1-2\beta_3/\left[\beta_1(1-\beta_1)\right]$. Housing productivity depends on Z^j and the unobserved residual, $\hat{A}_j^Y = -Z^j(\gamma) + \hat{A}_j^{0Y} - \varepsilon_j$.

The second-order approximation of the cost function (i.e. the translog) is not a constant-elasticity form. Hence, the elasticity of substitution 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.

Cobb-Douglas (CD) technology imposes the restriction $\sigma^Y = 1$, which in (7) is:

$$\beta_3 = \beta_4 = \beta_5 = 0. \tag{9}$$

Without additional data, non-neutral productivity differences are impossible to detect without knowing what shifts A_j^{YL}/A_j^{YM}. Here it seems reasonable to interact productivity

[11] Housing supply, as a quantity, is less responsive to price increases when substitutability is low, rather than when productivity is low.

shifters Z_j with the difference in input prices, $\hat{r}_j - \hat{\nu}_j$ in equation 7. The reduced-form model allowing for non-neutral productivity shifts, imposing the CRS restrictions, is:

$$\hat{p}_j - \hat{v}_j = \beta_1(\hat{r}_j - \hat{v}_j) + \beta_3(\hat{r}_j - \hat{v}_j)^2 + Z^j\gamma_1 + (\hat{r}_j - \hat{v}_j)\, Z^j\gamma_2 + \varepsilon_j \tag{10}$$

As shown in Appendix B, $\gamma_2 Z^j/2\beta_3 = \hat{A}_j^{YM} - \hat{A}_j^{YL}$ identifies observable differences in factor-biased technical differences. If $\sigma_Y < 1$, then $\gamma_2 > 0$ implies that the shifter Z lowers the productivity of land relative to the non-land input. Furthermore, we can see if the elasticity of substitution varies with Z^j by adding the term $(\hat{r}_j - \hat{v}_j)^2\, Z^j\gamma_3$.[12]

3.3 The Determination of Land and Non-Land Prices

We consider the equilibrium of a system of cities adapted from Albouy (2009). Land and non-land costs are determined simulataneously with housing prices from differences housing productivity, A_j^Y, trade-productivity, A_j^X, and quality of life, Q_j. Our first adaptation is that we assume each production sector has its own type of worker, $k = X, Y$, where type-Y workers produce housing. Preferences are represented by $U^k(x, y; Q_j^k)$, 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, which with non-labor income, I, makes up total income $m_j^k = w_j^k + I$, out of which federal taxes, $\tau(m_j^k)$ are paid.

Workers are mobile and both types occupy each city. Equilibrium requires that workers receive the same utility in all cities, $\bar{u}^k$ for each type. Log-linearized, this implies

$$\hat{Q}_j^k = s_y^k \hat{p}_j - (1 - \tau^k) s_w^k \hat{w}_j^k, \; k = X, Y. \tag{11}$$

i.e., quality of life offsets high prices or low wages, after taxes. Q_j^k is normalized such that $\hat{Q}_j^k$ of 0.01 is equivalent to a one-percent rise in total consumption, s_y^k is the housing expenditure share, and τ^k is the marginal tax rate, and s_w^k is labor's share of income. The aggregate quality-of-life differential is $\hat{Q}_j \equiv \mu^X \hat{Q}_j^X + \mu^Y \hat{Q}_j^Y$, where μ^k is the income share of type k, $s_y \equiv \mu^X s_y^X + \mu^Y s_y^Y$, and $(1 - \tau)\, s_w \hat{w} \equiv \mu^X (1 - \tau^X) s_w^X \hat{w}_j^X + \mu^Y (1 - \tau^Y) s_w^Y \hat{w}_j^Y$.

Traded output has a uniform price across cities and is produced with CRS and CD technology, with A_j^X being netural. We assume land commands the same price in both

[12] In equation 10, non-neutral productivity implies $\beta_1 = \phi_L + \beta_3(\hat{A}_{0j}^{YM} - \hat{A}_{0j}^{YL})$ and $\varepsilon^j = -[\phi^L \hat{A}_j^{YL} + (1 - \phi^L)\hat{A}_j^{YM}] + (12)\phi^L(1 - \phi^L)(1 - \sigma^Y)(\hat{A}_j^{YL} - \hat{A}_j^{YM})^2$. We normalize $(\hat{A}_{0j}^{YM} - \hat{A}_{0j}^{YL}) = 0$. Note that we do not find interactions for the quadratic interaction to be significant and thus have left a heterogenous elasticity of substitution out of the remainder of the analysis.

sectors. A derivation similar to (3) yields that the trade-productivity differential is

$$\hat{A}_j^X = \theta^L \hat{r}_j + \theta^N \hat{w}_j^X, \tag{12}$$

a weighted sum of factor-price differentials, where $\theta^L$and θ^N are corresponding cost shares.

Non-land inputs are produced according to $M_j = (N^Y)^a (K^Y)^{1-a}$, which implies $\hat{v}_j = a\hat{w}_j^Y$, where a is the cost-share of labor in non-land inputs. Defining $\phi^N = a(1-\phi^L)$, we can derive an alternative measure of housing productivity based on wages:

$$\hat{A}_j^Y = \phi^L \hat{r}_j + \phi^N \hat{w}_j^Y - \hat{p}_j. \tag{13}$$

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

Combining the equations 11, 12, and 13, the land-value differential times the income share of land, $s_R = s_x\theta_L + s_y\phi_L$, equals the sum of the weighted productivity and quality-of-life differentials minus the federal-tax differential, $\tau s_w \hat{w}_j$:

$$s_R \hat{r}_j = s_x \hat{A}_j^X + s_y \hat{A}_j^Y + \hat{Q}_j - \tau s_w \hat{w}_j. \tag{14}$$

Land thus fully capitalizes the value of local amenities minus federal tax payments.

3.4 Identification

Our econometric specification in equation 7 regresses housing costs $\hat{p}_j$ on land values $\hat{r}_j$, construction prices $\hat{v}_j$, and geographic and regulatory constraints, Z_j. The model in (4) implies the error term is the unexplained component of housing productivity, i.e., $\varepsilon_j = -\hat{A}_j^Y - Z_j\gamma$, although it could also reflect measurement error, market power in the housing sector, or disequilibrium forces causing prices to deviate from costs.

The geographic constraints are predetermined, so we treat them as exogenous. We also treat the regulatory constraints as exogenous: like most researchers, we have not found an instrument for regulations that we believe to be both relevant and excludable. While regulations may be endogenous to housing prices, stories that support that argument are less clear after conditioning on land values, construction costs, and geography. The prediction that constraints imply high housing values *relative* to land and non-land input prices is a novel, falsifiable prediction that has yet to be tested in the literature.

Identification requires that land values are uncorrelated with unobserved determinants of A_j^Y in the residual, ε_j. But, as equation 14 demonstrates, land values increase with housing productivity. Therefore, ordinary least squares (OLS) estimates will exhibit bias if the vector of characteristics Z_j is incomplete and $E[\varepsilon_j|Z_j] \neq 0$. This bias depends on the unknown covariance structure between $\hat{A}_j^X$,$\hat{A}_j^Y$, and $\hat{Q}_j$. OLS estimates will be best if the most of the variation in land values is driven by trade-productivity (i.e., jobs) and quality of life, and our measures of Z_j are rather exhaustive.[13]

An alternative is to find instrumental variables (IVs) for land values, as well as non-land input prices. Equation 14 suggests that variables that influence tradeable productivity A_j^X or quality of life Q^j should affect land values. Equation 4 shows that to satisfy the exclusion restriction such variables must be unrelated to housing productivity A_j^Y. 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_X^j. The second is an adaptation of the U.S. Department of Agriculture's "Natural Amenities Scale" (McGranahan 1999), which ought to correlate with Q^j.[14]

3.5 Dynamics and Option Value

In a dynamic model with certainty, Arnott and Lewis (1979) demonstrate that our static model produces consistent estimates with endogenous development. With uncertainty, the irreversibility of residential investment may impart a real option value to land, as owners of undeveloped land can decide not to proceed with development if market conditions evolve unfavorably. Thus, developers may build less often in areas where house prices are more volatile (see Capozza and Helsley 1990). If house prices are more volatile in supply-constrained areas, this option value may be correlated with more stringent land-use regulations. Thus, real option value could account for a portion of our estimated efficiency costs. Since this enhanced option value is due to constraints, it may be considered an additional cost from them. Regulations may also "follow the market" (Wallace 1988), potentially limiting their effects on land and housing prices, and the inefficiencies we estimate.

[13] Related problems arise with the determination of non-land prices v_j. Simulations in Albouy (2009) suggest these prices are only slightly affected by home productivity.

[14] The natural amenities index in McGranahan (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 instrumental variable because they are similar to the components of Saiz's (2010) index of geographic constraints 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

4.1 Land Values

CoStar COMPS Database

We calculate our land-value index from transactions prices recorded in the CoStar COMPS database between 2005 and 2010. The CoStar Group provides commercial real estate information and claims to have the industry's largest research organization.[15] Appendix A describes the sample selection criteria. CoStar provides a field describing the "proposed use" of each property. We use 12 of the most common categories, which are neither mutually exclusive nor collectively exhaustive.

Median and mean per-acre prices are \$272,838 and \$1,536,374. Median lot size is 3.5 acres versus a mean of 26.4 acres. Land sales occur more frequently in the beginning of our sample period, with 21.7% of our sample from 2005 and 11.4% from 2010. The frequencies of proposed uses are reported in table 1. Residential uses are common but by no means predominant in the sample: 17.5% of properties have a proposed use of single-family, multi-family, or apartments. 23.4% is being held for development or investment, and 15.9% of the sample had no listed proposed use.

Index of Metropolitan Land Values

We calculate the metropolitan index of land values by regressing the log price per acre of each sale, $\ln \tilde{r}_{ijt}$ on a set of a vector of controls, X_{ijt}, and a set of indicator variables for each year-MSA interaction, ψ_{jt} in the equation $\ln \tilde{r}_{ijt} = X_{ijt}\beta + \psi_{jt} + e_{ijt}$. We normalize estimates of ψ_{jt} to have a national average of zero, weighting by the number of housing units, to create year-by-MSA indices, $\hat{r}_{jt}$, used in our regression tables. For summary statistics and figures, we report indices, $\hat{r}_j$, aggregated across years.

Land-value indices derived from metro areas with fewer land sales may exhibit excess dispersion because of sampling error. We correct our estimates using shrinkage methods described in Kane and Staiger (2008), accounting for yearly as well as metropolitan variation in the estimated $\hat{\psi}_{jt}$. These methoods correct for mild amounts of attenuation bias.

Table 1 reports the results for four successive land-value regressions. The first includes only MSA and year-of-sale indicators. In column 2, we control for log lot size in acres, which improves the R^2 substantially from 0.30 to 0.70. The coefficient on lot size is -0.66, illustrating the "plattage effect," documented by Colwell and Sirmans (1978, 1980).

[15] The COMPS database provided by CoStar University, which is free of charge for academic researchers, includes transaction details for all types of commercial real estate.

In column 3, we add controls for intended use raising the R^2 to 0.71. These intended uses help to control for various characteristics of the land parcels, although ultimately their inclusion has little impact on our land-value index. In column 4 we weight the parcels to reflect the geographical distribution of housing units within each MSA as discussed in Appendix A; this regression provides our preferred inter-metropolitan index of land values.

Sample Selection, Potential Bias, and Remedies

The land parcels are based on observed transactions and are not randomly selected. As Nichols et al. (2013) discuss, it is impossible to correct for possible selection bias without observing prices for unsold lots. Fortunately, the literature has generally found selection bias to be surpisingly minor for land and commercial real estate prices.[16]

To help readers assess the gravity of these concerns, Figure 2 maps the locations of our land sales in the New York, Los Angeles, Chicago, and Houston metro areas. The figure shows that land sales are spread throughout these metro areas, and sales activity appears to be more intense near city centers, where residential densities are high.[17] An additional resource for readers to assess the plausibility of the estimates is appendix table A3, which lists every metro area in our sample ranked by estimated land values.

One potential source of selection bias is that we may be more likely to observe land sales on the urban fringe, where development activity is more intense. Such land will more closely reflect agricultural land values, attenuating measured land-value differences across cities. Such selection bias would likely lead us to overestimate the cost share of land in housing by reducing the estimated inter-metropolitan variation in land values, increasing the perceived housing-to-land value gradient. If this bias becomes increasingly worse in high-value areas, it could bias the estimated elasticity of substitution towards zero. Such biases should, however, cause our specification tests using construction costs to fail.

Our preferred land-value index uses the shrunken and weighted estimators based on all land sales, as described above. Appendix A discusses this choice relative to alternatives.

[16]Colwell and Munneke (1997), studying land prices in Cook County, Illinois, report, "The estimates with the selection variable and those without are surprisingly consistent for each land use." Munneke and Slade study possible selection bias in the Phoenix office market using two different methodologies and find (2000): "...the price indices generated after correcting for sample-selection bias do not appear significantly different from those that do not consider selectivity bias", and (2001): "Little selection bias is found in the estimates." Finally, Fisher et al. (2007), in their study of the National Council of Real Estate Investment Fiduciaries Property Index, which tracks commercial real estate properties, find "...sample selection bias does not appear to be an issue with our annual model specification."

[17]This observation mirrors that of Haughwout et al. (2008), who analyze the CoStar data for New York and write: "Overall, vacant land transactions occurred throughout the region, with a heavy concentration in the most densely developed areas ...".

Land values for a selected group of metropolitan areas are reported in table 2. The weighted standard deviation across MSAs is 76 log points. In general, large, coastal cities have the highest land values, while smaller cities in the South and Midwest have lower values. The New York metro area has the highest land values, which are 35 times higher than those in Rochester, NY, which has the lowest. This range is approximately \$9,000 to \$320,000 for a standard fifth-acre residential lot (at the median) across metros. Overall, the inter-metropolitan land value index appears quite reasonable.

4.2 Housing Prices, Wages, and Construction Prices

We calculate housing-price and wage indices for each year from 2005 to 2010 using the 1% samples from the American Community Survey. Our method, described fully in Appendix C, mimics that for land values. We aggregate our inter-metropolitan index of housing prices, $\hat{p}_{jt}$, normalized to have mean zero, across years for display.

We estimate wage levels in a similar fashion, controlling for worker skills and characteristics, for two samples: all workers, $\hat{w}_j$, and for the purpose of our cost estimates, workers in the construction industry only, $\hat{w}_j^Y$. As seen in appendix figure D, $\hat{w}_j^Y$ is similar to, but more dispersed than, overall wages, $\hat{w}_j$.[18]

Our main price index for construction inputs comes from the Building Construction Cost data from the RS Means company, which is common in the literature, e.g., Davis and Palumbo (2008), and Glaeser et al. (2005b). Appendix C discusses the construction price index in more detail.

The equilibrium condition for housing requires equation 2 to hold, so that the replacement cost of a housing unit equals its market price. Because housing is durable, this condition may not bind in cities where housing demand is so weak that there is effectively no new supply (Glaeser and Gyourko 2005). In this case, replacement costs will be above market prices, biasing the estimate of A_j^Y upwards. Technically, there is new housing supply in all of the MSAs in our sample, as measured by building permits. However, we suspect that the equilibrium condition may not bind throughout metro areas where population growth has been low. To indicate MSAs with weak growth, we mark with an asterisk ($*$) MSAs where the population growth between 1980 and 2010 is in the lowest decile of our sample, weighted by 2010 population. These include metros such as Pittsburgh, Buffalo, and Detroit. In Appendix D, we find that the results do not change meaningfully when we exclude

[18]We estimate wage levels at the CMSA level to account for commuting behavior across PMSAs.

these areas. Nevertheless, estimates of housing productivity in such areas require caution.

The housing-price, construction-wage, and construction-cost indices, reported in columns 2, 3, and 4 of table 2, are strongly related to city size and positively correlated with land values. They also exhibit considerably less dispersion. The highest housing prices are in San Francisco, which are 9 times the lowest housing prices, in McAllen, TX. This implies a range of about \$75,000 to \$675,000 for a typical (median) five-room unit. The highest construction prices are in New York City, 1.9 times the lowest, in Rocky Mount, NC.

4.3 Regulatory and Geographic Constraints

Our index of regulatory constraints comes from the Wharton Residential Land Use Regulatory Index (WRLURI), described in Gyourko, Saiz, and Summers (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.[19] 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 times each municipality's population weight within its MSA. The authors construct a single aggregate WRLURI index through factor analysis: we consider both the aggregate index and the subindices in our analysis, each of which we renormalize as $z-$scores, with a mean of zero and standard deviation one, as weighted by the housing units in our sample. The WRLURI subindices are typically, but not always, positively correlated with one another.

Our index of geographic constraints 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 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.

Table A3 shows that the most regulated land is in Boulder, CO, and the least regulated is in Mobile, AL; the most geographically constrained is in Santa Barbara, CA, and the least is in Lubbock, TX.

[19]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

Below, we use the indices from section 4 to test and estimate the cost function presented in section 3, and examine how it is influenced by geography and regulation using both aggregated and disaggregated measures. 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 206 MSAs and 856 MSA-years. Regressions are weighted by the number of housing units.

5.1 Estimates and Tests of the Model

Figure 1C plots metropolitan housing prices against land values. The simple regression line's slope of 0.59 would estimate the cost share of land, ϕ_L, assuming CD production, if there were no other cost or productivity differences across cities. The convex curvature in the quadratic regression implies land costs increase with land values, yielding an imprecise estimate of the elasticity of substitution of 0.18.[20] This figure illustrates how the vertical distance between a marker and the regression line forms the basis of our estimate of housing productivity. Accordingly, San Francisco has low housing productivity and Las Vegas has high housing productivity. These regressions are biased, as land values are positively correlated with construction prices and geographic and regulatory constraints.

To illustrate construction prices, we plot them against land values in figure 3A. We use these data to estimate a cost surface shown in figure 3B without controls. As in figure 1C, cities with housing prices above this surface are inferred to have lower housing productivity. Figure 3A plots the level curves for the surface in 3B, which correspond to the zero-profit conditions (ZPCs) for housing producers, seen in equation (4). These curves correspond to fixed sums of housing prices and productivities, $\hat{p}_j + \hat{A}_j^Y$. Curves further to the upper-right correspond to higher sums. With the log-linearization, the slope of the ZPC is the ratio of land cost shares to non-land cost shares, $-\phi_j^L/(1-\phi_j^L)$. The solid line illustrates the CD case, with constant slope. The concave dashed curves illustrate the case with an elasticity, σ^Y, less than one, as land's relative cost-share increases with land values.

Columns 1 and 2 of table 3 present more complete cost-function estimates using the aggregate geographic and regulatory indices, assuming CD production, as in 9. Column 2 imposes the restriction of CRS in 8, which is rejected at the 5% level. The CRS restriction

[20] In levels, the cost curve must be weakly concave, but the log-linearized cost curve is convex if $\sigma^Y < 1$, although the convexity is limited as $\sigma^Y \geq 0$ implies $\beta_3 \leq 0.5\beta_1(1-\beta_1)$.

is not rejected in the more flexible translog equation, presented in columns 3 and 4. The restricted regression in column 4 estimates the elasticity of substitution σ^Y to be 0.35.

The OLS estimates in columns 1 through 4 produce stable values of 0.34-0.38 for the cost-share of land parameter, ϕ_L. Furthermore, we find that one standard deviation increases in the geographic and regulatory indices predict a 9- and 7-percent increases in housing costs, respectively. These effects are consistent with our theory of housing productivity and the belief that geographic and regulatory constraints impede the production of housing services.

Columns 5 and 6 present IV estimates, which use our two instruments and their squares as instruments for the differentials $(\hat{r} - \hat{v})$ and $(\hat{r} - \hat{v})^2$. Column 5 imposes the CD restriction, and only uses the instrument levels. Table A1 presents first-stage estimates including assessments of instrument strength and validity. The IV estimates are largely consistent with our OLS estimates, although they suggest a somewhat higher cost share of land and are less precise. The last row of table 3 reports results of Wooldridge's (1995) test of regressor endogeneity: these tests do not reject the null of regressor exogeneity at the 5% confidence level. The consistency of the IV estimates requires that distance-to-coast and amenity scores are uncorrelated with housing productivity, conditional on measures of geography and regulation. This assumption may not hold, for instance if it is inefficient to build housing in extreme temperatures. To assess these concerns, we perform overidentification tests of the instruments' exogeneity as in Sargan (1958).[21] In both cases, we are unable to reject the null hypothesis that the instruments are exogenous.

We test the assumption that the productivity shifters are factor neutral in column 7. This allows γ_2 to be non-zero in equation (10) by interacting the differential $(\hat{r} - \hat{v})$ with the geographic and regulatory indices. The positive estimated interaction with land-use restrictions suggest that they particularly impede the efficient use of land.[22]

Finally, column 8 uses wage levels in the construction industry instead of the construction prices. The results in column 8 are similar to those in column 4. The CRS restriction fails at standard significance levels. These results cross-validate our results using construction prices, while suggesting that construction prices vary for reasons other than construction-sector wages.

We perform a number of additional robustness checks in table A2. We split the sam-

[21]Performing those tests requires us not to cluster the standard errors at the CMSA level, which should cause the tests to be more conservative.

[22]Estimates for whether constraints affect the elasticity of substitution, using a quadratic interaction, are not significant statistically or economically.

ple into two periods: a "housing-boom" period, from 2005 to 2007, and a "housing-bust" period, from 2008 to 2010. We also use alternative land-value indices, one using only residential land, a second not controlling for proposed use or lot size, and another not shrinking the land-value index. The last two robustness checks drop observations in our low-growth areas. The results of these robustness checks, discussed in Appendix D, reveal that the regression parameters are surprisingly stable over these specifications. The stability of estimates across the boom and bust periods are consistent with Albouy and Ehrlich (2013), who find that land values vary over time much less than over space, and that interactions between space and time over this period are relatively unimportant.

5.2 Disaggregating the Regulatory and Geographic Indices

As discussed above, the WRLURI aggregates 11 subindices, while the Saiz index aggregates two. Column 1 of table 4 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 4 of table 3, but with the disaggregated regulatory and geographic subindices. The results indicate that one-standard deviation increases in state political and state court involvement reduce metro-level productivity by 4 to 5 percent. Average local political pressure, local project approval and local political pressure each appear to reduce productivity by 2 to 3 percent. The results at the local level, each with p-values less than 0.08, may be weaker than those at the state level, with p-values than 0.03, as many local constraints may be avoided within a metro area by switching communities. Approval delay is not significant, although the point estimate suggests that a one-year delay (two standard deviations) increases costs by 3.2 percent, consistent with a standard discount rate. The remaining five coefficients are also insignificant, although the almost significant negative coefficient on exactions is surprising and suggests that areas with them may otherwise efficient land-use regulation (Yinger 1998). The regression coefficients are positively related to, albeit somewhat differnt from, the factor loadings.

Both of the Saiz subindices have statistically and economically significant negative point estimates, indicating a one standard-deviation increase in the share of flat or solid land is associated with a 7- to 9-percent reduction in housing costs.

The tight fit of the cost-function specification, as measured by the R^2 values approaching 80 percent, implies that even our imperfect measures of input prices and observable constraints explain the variation in housing prices across metros quite well. The estimated cost share of land and the elasticity of substitution are quite plausible, and most of the coefficients on the regulatory and geographic variables have the predicted signs and reasonable magnitudes. We take column 4 of table 4 as our favored specification– with CRS, factor-neutrality, non-unitary σ^Y, and disaggregated subindices – and use it for our subsequent analysis. It provides a value of $\phi_L = 0.35$ and $\sigma^Y = 0.56$. Using formula 5, the typical cost share of land ranges from 16 percent in Rochester to 49 percent in New York City.

6 Housing Productivity across Metropolitan Areas

6.1 Productivity in Housing and Tradeables

In column 1 of table 5 we list the inferred measures of housing productivity from our favored specification, using both observed and unobserved components of housing productivity, i.e., $\hat{A}_j^Y = Z_j(-\hat{\gamma}) - \hat{\varepsilon}_j$; column 2 reports only the value of productivity predicted by the regulatory subindices, Z_j^R, i.e., $\hat{A}_j^{YR} = -\hat{\gamma}_1^R Z_j^R$. The cities with the most and least productive housing sectors are McAllen, TX and San Luis Obispo, CA. Among large metros, with over one million inhabitants the top five, excluding our low-growth sample, are Houston, Indianapolis, Kansas City, Fort Worth, and Columbus; the bottom five are San Francisco, San Jose Oakland, Los Angeles, and Orange County, all on California's coast. Along the East Coast, Bergen-Passaic (Northern New Jersey) and Boston are notably unproductive. Cities with average productivity include Phoenix, Chicago, Miami. and the New York PMSA, which includes all five boroughs and Westchester county.[23]

Estimates of trade productivity $\hat{A}_j^X$ and quality-of-life $\hat{Q}_j$ are in columns 3 and 4, based on formulas (12) and (11), calibrated with parameter values taken from Albouy (Forthcoming). Figure 4 plots housing productivity relative to trade-productivity. The figure draws a level curves for total productivity, as well as a curve that delineates the bias in trade-productivity measures if housing-prices are used instead of land values, asssuming

[23] See Table A3 for the values of the major indices and measures for all of the MSAs in our sample.

$\hat{A}_Y^j = 0$.[24]

Our estimates of trade-productivity, based primarily on overall wage levels, are largely consistent with the previous literature. Interestingly, trade productivity and housing productivity are negatively related. A 1-point increase in trade-productivity predicts a 1.6-point decrease in housing productivity. For instance, cities in the San Francisco Bay Area have among the highest levels of trade productivity and the lowest levels of housing productivity. On the other hand, Houston, Fort Worth, and Atlanta are relatively more productive in housing than in tradeables. The large metro area with the greatest overall productivity is New York; that with the least is Tucson.[25]

The negative relationship between trade and housing productivity estimates may stem from differing scale economies at the city level. While trade-productivity is known to increase with city size (e.g., Rosenthal and Strange, 2004), it is possible that economies of scale in housing may be decreasing, possibly because of negative externalities in production from congestion, regulation, or other sources. It may be more difficult for producers to build new housing in already crowded environments, such as on a lot surrounded by other structures.

New construction may impose negative externalities in consumption on incumbent residents, e.g., by blocking views or increasing traffic. Aware of this, residents in populous areas may seek to constrain housing development to limit these externalities through regulation, as discussed below, lowering housing productivity.

Table 6 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 of

[24]These calibrated values are $\theta^L = 0.025$, $s_w = 0.75$, $\tau = 0.32$, $s_x = 0.64$. θ^N is set at 0.8 so that it is consistent with s_w. For the estimates of $\hat{Q}_j$, we account for price variation in both housing and non-housing goods. We measure cost differences in housing goods using the expenditure-share of housing, 0.18, times the housing-price differential $\hat{p}_j$. To account for non-housing goods, we use the share of 0.18 times the predicted value of housing net of productivity differences, setting $\hat{A}_Y^j = 0$, i.e., $\hat{p}_j - \hat{A}_Y^j = \phi_L \hat{r}_j + \phi_N \hat{w}_j$, the price of non-tradeable goods predicted by factor prices alone. Furthermore, we subtract a sixth of housing-price costs to account for the tax-benefits of owner-occupied housing. This procedure yields a cost-of-living index roughly consistent with that of Albouy (2008). Our method of accounting for non-housing costs helps to avoid problems of division bias in subsequent analysis, where we regress measures of quality of life, inferred from high housing prices, with measures of housing productivity, inferred from low housing prices. The bias in trade-productivity without land measures is given by $\theta_L/\phi_L \hat{A}_Y$, and is implicit in similar measures of trade-productivity that conflate land and housing, e.g. Beeson and Eberts (1989) and Shapiro (2006).

[25]The housing productivity estimates are positively related to the housing supply elasticities provided by Saiz (2010): a 1-point increase in productivity predicts 2.25-point (s.e. = 0.24) increase in the supply elasticity.

roughly 6 percent are consistent with those in the literature. The results in column 2 reveal elasticities of nearly negative 7 percent. According to the results in column 3, which uses only the housing productivity component predicted by the regulatory subindices, about one third of this relationship results from greater observed regulation. Overall productivity, examined in column 4, increases with population, but much less than trade productivity. The results in column 5 suggest that this relationship would be stronger if the greater regulation associated with higher populations were held constant. As we explore in the next section, however, holding the regulatory environment constant could have negative consequences for urban quality of life.

6.2 Housing Productivity and Quality of Life

The model in 3 predicts that if regulations only reduce housing productivity, then they will increase housing prices and reduce land values, unambiguously lowering welfare (Albouy, 2009). 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, zoning raises house prices by increasing demand, rather than by limiting supply. To our knowledge, there are only a few estimates of the benefits of these regulations, e.g. Cheshire and Sheppard (2002) and Glaeser et al. (2005b), both of which suggest that the welfare costs of regulations outweigh their benefits.

To examine this hypothesis we relate our quality-of-life and housing-productivity estimates, shown in figure 5. The simple regression line in this figure suggests that a one-point decrease in housing productivity is associated with a 0.1-point increase in quality of life. If we accept the relationship as causal, the net welfare benefit of this trade-off, measured as a fraction of total consumption, equals this 0.1-point increase, minus the the expenditure share of housing, whose costs are driven up a full percentage point. If the expenditure share of housing is 0.15 of household income, a one-point decrease in housing productivity would then result in a net welfare loss equivalent to 0.05-percent of consumption. This estimate must be treated cautiously as places with intrinsically higher quality of life may be more prone to regulate.

Welfare-reducing regulations may be rationalized if the 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.[26]

We explore this relationship further in table 7, which controls for possible confounding factors and isolates housing productivity predicted by regulation. Columns 1 and 3 include controls for natural amenities, such as climate, adjacency to the coast, and the geographic constraint index; columns 2 and 4 add controls for artificial amenities, such as the population level, density, education, crime rates, and number of eating and drinking establishments. In columns 1 and 2, these controls undo the relationship, as geographic amenities are related negatively to productivity and positively to quality of life. When we focus on productivity predicted by regulation, in columns 3 and 4, the relationship from figure 5 reappears, although weakly and insignificantly. These results suggest that land-use regulations reduce net welfare substantially.

A one-standard deviation decrease in productivity costs due to regulations is 10.4 percent. According to the most charitable specification in column 3, this produces quality of life benefits equal to 0.4 percent of income, or about \$280 annually for a household with an average income of \$71,000. The additional housing costs cause an income loss of 1.56 percent of income, or \$1,110 annually. Alternatively, the typical regulation produces 25 cents of benefit per dollar of cost. These results imply that regulations applied at the metro level will typically lower the value of land while raising the cost of housing.

Non-causal explanations for the relationship in table 7 are also plausible. For instance, residents in areas with unobserved amenities may simply elect to regulate land-use for reasons unrelated to urban quality of life. Alternatively, with preference heterogeneity, the quality-of-life measure represents the willingness-to-pay of the marginal resident. In cities with low-housing productivity, the supply of housing is effectively constrained, raising the willingness-to-pay of the marginal resident, much as in the "Superstar City" hypothesis of Gyourko, Mayer, and Sinai (2013). However, the negative relationship between productivity and quality of life appears to hold for more than a small subset of cities.

7 Conclusion

The novel index of land values assembled here contains important information independent from, yet compatible with, more common indices of housing prices. The CES quadratic

[26]The net welfare loss from regulations implies that land should lose value while housing gains value. While property owners should in the long run seek to maximize the value of their land, frictions, due to moving costs and the immobility of housing capital, may cause most owners to maximize the value of their housing stock over their voting time horizons.

cost function model passes the necessary tests, validating the compatibility of our disparate land-value, construction-cost, and housing-price indices. Moreover, the cost function fits the data well and produces estimates with credible economic magnitudes. The two input-price and two constraint measures together explain 75 percent of the variation in home prices. Using 11 regulatory and two geographic subindices explains 79 percent. Furthermore, our instrumental variable estimates suggest that our ordinary least squares estimates are likely to be consistent.

The average cost share of land in housing is about one-third and the elasticity of substitution between land and non-land inputs is roughly one-half, well in the middle of other estimates, implying the typical cost share of land ranges from 15 to 50 percent across metros. The estimates support the hypothesis that geographic and regulatory constraints create a wedge between the prices of housing and its inputs, quantifying their impacts. The disaggregated estimates suggest that state political and court involvement are associated with large increases in particularly housing costs, which is consistent with the difficulty of avoiding them.

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. These regulatory costs are, at best, weakly associated with a higher quality of life for residents. Thus, land-use regulations appear to raise housing prices more by restricting supply than by increasing demand. On net, the typical land-use regulation reduces well-being by making housing less affordable.

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TABLE 1: LAND VALUE INDEX REGRESSIONS

	Fraction of Sample	Dependent Variable: Log Price per Acre			
	(0)	(1)	(2)	(3)	(4)
Log lot size (acres)			-0.660	-0.647	-0.597
			(0.002)	(0.002)	(0.003)
No proposed use	15.9%			-0.198	-0.332
				(0.012)	(0.014)
Proposed use: commercial	0.3%			-0.369	-0.252
				(0.064)	(0.077)
Proposed use: industrial	7.5%			-0.316	-0.522
				(0.015)	(0.019)
Proposed use: retail	8.1%			0.260	0.211
				(0.014)	(0.017)
Proposed use: single-family	10.7%			-0.020	-0.188
				(0.014)	(0.020)
Proposed use: multi-family	3.3%			-0.071	-0.174
				(0.021)	(0.019)
Proposed use: office	6.3%			0.072	0.185
				(0.016)	(0.020)
Proposed use: apartment	3.6%			0.468	0.366
				(0.021)	(0.016)
Proposed use: hold for development	19.2%			-0.069	-0.085
				(0.013)	(0.013)
Proposed use: hold for investment	4.3%			-0.358	-0.287
				(0.020)	(0.027)
Proposed use: mixed use	4.3%			0.373	0.407
				(0.028)	(0.027)
Proposed use: medical	1.0%			0.162	-0.038
				(0.038)	(0.051)
Proposed use: parking	0.9%			0.181	0.253
				(0.039)	(0.033)
Number of Observations		68,757	68,757	68,757	68,757
Adjusted R-squared		0.301	0.699	0.711	0.762
Weighted by Predicted Density		No	No	No	Yes

Robust standard errors, clustered by MSA/PMSA, reported in parentheses. Land-value data from CoStar COMPS database for years 2005 to 2010. All specifications include a full set of interacted MSA and year-of-sale indicators (not shown). Predicted density is number of land sales predicted by a geographical model of housing units relative to city center; please see appenedix A for a full description.

TABLE 2: MEASURES FOR SELECTED METROPOLITAN AREAS, RANKED BY LAND-VALUE DIFFERENTIAL: 2005-2010

Name of Area	Population	Observed No. of Land Sales	Land Value	Housing Price	Wages (Const. Only)	Const. Price Index	Regulation Index (z-score)	Geo Unavail. Index (z-score)	Land Value Rank
Metropolitan Areas:									
New York, NY PMSA	9,747,281	1,603	1.68	0.84	0.25	0.31	-0.22	0.56	1
San Francisco, CA PMSA	1,785,097	152	1.50	1.29	0.21	0.23	1.68	2.17	3
San Jose, CA PMSA	1,784,642	217	1.31	1.08	0.21	0.18	-0.11	1.71	4
Orange County, CA PMSA	3,026,786	233	1.24	0.93	0.12	0.10	0.03	1.15	5
Los Angeles-Long Beach, CA PMSA	9,848,011	1,760	1.01	0.86	0.12	0.10	0.84	1.15	7
Washington, DC-MD-VA-WV PMSA	5,650,154	1,840	0.72	0.39	0.18	0.01	0.85	-0.74	16
Boston, MA-NH PMSA	3,552,421	122	0.52	0.62	0.10	0.18	1.26	0.24	21
Chicago, IL PMSA	8,710,824	3,511	0.25	0.14	0.06	0.17	-0.60	0.54	35
Phoenix-Mesa, AZ MSA	4,364,094	5,946	0.23	-0.03	-0.01	-0.10	0.96	-0.74	37
Philadelphia, PA-NJ PMSA	5,332,822	859	0.13	0.02	0.05	0.16	0.64	-0.93	43
Riverside-San Bernardino, CA PMSA	4,143,113	2,452	0.02	0.22	0.12	0.07	0.60	0.44	51
Atlanta, GA MSA	5,315,841	5,229	-0.15	-0.32	0.03	-0.10	0.03	-1.23	74
Houston, TX PMSA	5,219,317	1,143	-0.36	-0.54	0.04	-0.12	-0.12	-1.01	107
Dallas, TX PMSA	4,399,895	811	-0.40	-0.46	0.00	-0.14	-0.73	-0.98	114
Detroit, MI PMSA*	4,373,040	679	-0.45	-0.35	-0.04	0.05	-0.31	-0.22	118
Saginaw-Bay City-Midland, MI MSA*	390,032	41	-1.74	-0.63	-0.16	-0.03	-0.24	-0.62	216
Utica-Rome, NY MSA*	293,280	15	-1.81	-0.58	-0.27	-0.05	-1.50	-0.56	217
Rochester, NY MSA*	1,093,434	110	-1.88	-0.54	-0.07	0.01	-0.61	0.07	218
Metropolitan Population:									
Less than 500,000	31,264,023	1,378	-0.52	-0.23	-0.08	-0.44	-0.04	-0.05	4
500,000 to 1,500,000	55,777,644	3,253	-0.41	-0.20	-0.07	-0.34	-0.16	-0.06	3
1,500,000 to 5,000,000	89,173,333	8,168	0.16	0.07	0.01	0.13	0.17	0.01	2
5,000,000+	49,824,250	3,997	0.61	0.32	0.11	0.17	0.01	0.10	1
Standard Deviations (pop. wtd.)			0.76	0.51	0.16	0.14	0.96	1.01	
Correlation with land values (pop. wtd.)			1.00	0.89	0.66	0.60	0.46	0.57	

Land-value data 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 3: MODEL OF HOUSING COSTS WITH AGGREGATE GEOGRAPHIC AND REGULATORY INDICES

Specification	Basic Cobb-Douglas (1)	Restricted Cobb-Douglas (2)	Translog (3)	Restricted Translog (4)	Restricted Cobb-Douglas (Instr. Var.) (5)	Restricted Translog (Instr. Var.) (6)	Non-neutral Productivity Translog (7)	Restricted Translog w/ Constr Wages (8)
Land-Value Differential	0.360	0.375	0.342	0.376	0.484	0.451	0.385	0.361
	(0.037)	(0.034)	(0.041)	(0.036)	(0.082)	(0.080)	(0.031)	(0.032)
Construction-Price Differential	1.049	0.625	0.996	0.624	0.516	0.549	0.615	0.639
	(0.159)	(0.034)	(0.160)	(0.036)	(0.082)	(0.080)	(0.031)	(0.032)
Land-Value Differential Squared			0.033	0.076		0.060	0.067	0.072
			(0.033)	(0.034)		(0.113)	(0.029)	(0.031)
Construction-Price Differential Squared			-1.158	0.076		0.060	0.067	0.072
			(1.040)	(0.034)		(0.113)	(0.029)	(0.031)
Land-Value Differential X Construction-Price Differential			0.400	-0.152		-0.120	-0.134	-0.144
			(0.321)	(0.068)		(0.226)	(0.058)	(0.062)
Geographic Constraint Index: z-score	0.092	0.104	0.092	0.093	0.080	0.081	0.091	0.111
	(0.025)	(0.027)	(0.023)	(0.027)	(0.031)	(0.030)	(0.022)	(0.026)
Regulatory Index: z-score	0.058	0.068	0.072	0.075	0.047	0.059	0.081	0.063
	(0.013)	(0.013)	(0.013)	(0.014)	(0.024)	(0.024)	(0.014)	(0.015)
Geographic Constraint Index times Land Value Differential minus Construction Price Differential							0.050	
							(0.019)	
Regulatory Index times Land Value Differential minus Construction Price Differential							-0.018	
							(0.044)	
Number of Observations	856	856	856	856	206	206	856	888
Number of MSAs	207	207	207	207	206	206	207	217
Adjusted R-squared	0.855	0.724	0.864	0.745			0.746	0.731
p -value for CRS restrictions		0.006		0.122	0.059	0.191	0.060	0.005
p -value for CD restrictions	0.409	0.027						
p- value for all restrictions		0.017						
Elasticity of Substitution	1.000	1.000		0.349	1.000	0.517	0.431	0.380
				(0.278)		(0.916)	(0.242)	(0.257)
p-value of test of Land-Value differential exogeneity					0.077	0.628		

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 2. Restricted model specifications require that the production function exhibits constant returns to scale (CRS). 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. Instrumental variables are the inverse mean distance from the sea and an adapted USDA natural amenities score (McGranahan 1999); first-stage regressions are reported in table A1. Test of land-value differential engodeneity is from Wooldridge (1995).

TABLE 4: MODEL OF HOUSING COSTS WITH DISAGGREGATED GEOGRAPHIC AND REGULATORY INDICES

Specification	Regulatory Index Factor Loading			Restricted Translog w Cons Price
Dependent Variable		Reg Index	Geo Index	Hous. Price
	(1)	(2)	(3)	(4)
Land-Value Differential				0.354
				(0.031)
Land-Value Differential Squared				0.050
				(0.026)
Approval Delay: z-score	0.29	0.403		0.016
		(0.000)		(0.015)
Local Political Pressure: z-score	0.22	0.334		0.023
		(0.000)		(0.012)
State Political Involvement: z-score	0.22	0.403		0.049
		(0.000)		(0.019)
Open Space: z-score	0.18	0.162		-0.013
		(0.000)		(0.015)
Exactions: z-score	0.15	0.023		-0.024
		(0.000)		(0.014)
Local Project Approval: z-score	0.15	0.167		0.027
		(0.000)		(0.015)
Local Assembly: z-score	0.14	0.121		0.020
		(0.000)		(0.008)
Density Restrictions: z-score	0.09	0.194		0.012
		(0.000)		(0.015)
Supply Restrictions: z-score	0.02	0.089		0.010
		(0.000)		(0.007)
State Court Involvement: z-score	-0.03	-0.060		0.044
		(0.000)		(0.019)
Local Zoning Approval: z-score	-0.04	-0.036		-0.009
		(0.000)		(0.016)
Flat Land Share: z-score			-0.493	-0.091
			-(0.787)	(0.023)
Solid Land Share: z-score			-0.787	-0.067
			(0.059)	(0.023)
Number of Observations		890	890	856
Adjusted R-squared		1.000	0.846	0.789
Elasticity of Substitution				0.558
				(0.220)

Robust standard errors, clustered by CMSA, reported in parentheses. Regressions include constant term. Data sources are described in table 2; 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 5: INFERRED INDICES OF SELECTED METROPOLITAN AREAS, RANKED BY TOTAL AMENITY VALUE

	Housing Productivity				
	Total (Including Indices) (1)	Predicted by Regulation Subindices (2)	Trade Productivity (3)	Quality of Life (4)	Total Amenity Value (5)
Metropolitan Areas:					
New York, NY PMSA	0.026	-0.018	0.151	0.098	0.199
San Francisco, CA PMSA	-0.550	-0.180	0.204	0.089	0.120
San Jose, CA PMSA	-0.458	-0.025	0.199	0.068	0.113
Orange County, CA PMSA	-0.385	-0.042	0.097	0.094	0.087
Los Angeles-Long Beach, CA PMSA	-0.424	-0.124	0.091	0.076	0.058
Washington, DC-MD-VA-WV PMSA	-0.120	-0.042	0.117	0.022	0.075
Boston, MA-NH PMSA	-0.331	-0.231	0.087	0.032	0.028
Chicago, IL PMSA	0.033	0.086	0.049	0.005	0.042
Phoenix-Mesa, AZ MSA	0.032	-0.117	-0.004	0.017	0.020
Philadelphia, PA-NJ PMSA	0.114	0.021	0.055	-0.011	0.045
Riverside-San Bernardino, CA PMSA	-0.187	-0.087	0.066	-0.016	-0.008
Atlanta, GA MSA	0.184	0.030	-0.015	-0.023	0.000
Houston, TX PMSA	0.314	0.070	-0.001	-0.053	0.003
Dallas, TX PMSA	0.211	0.099	-0.023	-0.043	-0.020
Detroit, MI PMSA*	0.214	-0.026	-0.015	-0.042	-0.013
Fort Smith, AR-OK MSA	0.089	0.166	-0.217	-0.046	-0.169
Rochester, NY MSA*	0.038	0.009	-0.122	-0.118	-0.189
Glens Falls, NY MSA	-0.240	0.100	-0.125	-0.082	-0.204
Metropolitan Population:					
Less than 500,000	0.000	0.016	-0.063	-0.024	-0.065
500,000 to 1,500,000	0.021	0.023	-0.052	-0.020	-0.049
1,500,000 to 5,000,000	-0.016	-0.016	0.015	0.009	0.016
5,000,000+	-0.022	-0.005	0.073	0.028	0.071
United States	0.226	0.133	0.089	0.048	0.074
		standard deviations (population weighted)			

Housing productivity, in column 1 is calculated from the specification in column 4 of table 4, as the negative of the sum of the regression residual plus the housing price predicted by the WRLURI and Saiz subindices. Housing productivity predicted by regulation is based upon the projection of housing prices on the WRLURI subindices. Trade productivity is calculated as 0.8 times the overall wage differential plus 0.025 times the land-value differential. Refer to section 5 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 6: PRODUCTIVITY IN TRADEABLE AND HOUSING SECTORS ACCORDING TO METROPOLITAN POPULATION AND DENSITY

	Dependent Variable				
	Trade Productivity (1)	Housing Productivity (2)	Hous. Prod. Predicted by Regulation (3)	Total Productivity (4)	Total Productivity No Reg. (5)
Panel A: Population					
Log of Population	0.056	-0.068	-0.024	0.024	0.028
	(0.004)	(0.023)	(0.007)	(0.004)	(0.004)
Number of Observations	207	207	207	207	207
Adjusted R-squared	0.649	0.146	0.101	0.474	0.563
Panel B: Population Density					
Weighted Density Differential	0.064	-0.066	-0.027	0.029	0.034
	(0.004)	(0.030)	(0.010)	(0.004)	(0.004)
Number of Observations	207	207	207	207	207
Adjusted R-squared	0.442	0.072	0.064	0.369	0.427

Robust standard errors, clustered by CMSA, reported in parentheses. Trade and housing productivity differentials are calculated as in table 5. Total productivity is calculated as 0.18 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.

TABLE 7: QUALITY OF LIFE AND HOUSING PRODUCTIVITY

	Dependent Variable: Quality of Life			
Housing Productivity Measure:	Total Housing Productivity		Housing Productivity Predicted by Regulation	
	(1)	(2)	(3)	(4)
Housing Productivity	0.023	0.057	-0.038	-0.012
	(0.033)	(0.023)	(0.029)	(0.029)
Natural Controls	X	X	X	X
Artificial Controls		X		X
Number of Observations	201	201	201	201
Adjusted R-squared	0.54	0.74	0.54	0.73

Robust standard errors, clustered by CMSA, in parentheses. Quality of life is calculated as in table 6. Housing productivity predicted by regulation is calculated as in table 5. Natural controls: heating and cooling degree days, July humidity, annual sunshine, annual precipitation, adjacency to coast, geographic constraint index. Artificial controls include metropolitan population, density, eating and drinking establishments, violent crime rate, and fractions with a college degree, some college, and high-school degree. Both sets of controls are from Albouy et al. (2012).

Figure 1A: The effect of low productivity or low substitutability on housing prices in levels

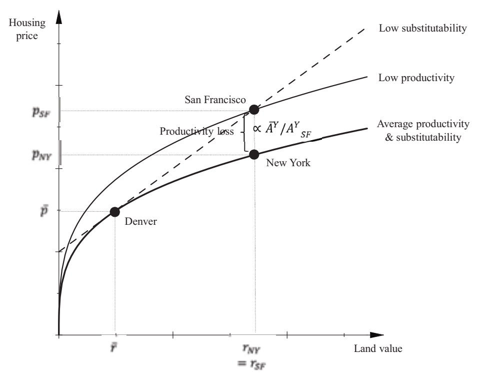


Figure 1B: The effect of low productivity or low substitutability on housing prices in logarithms

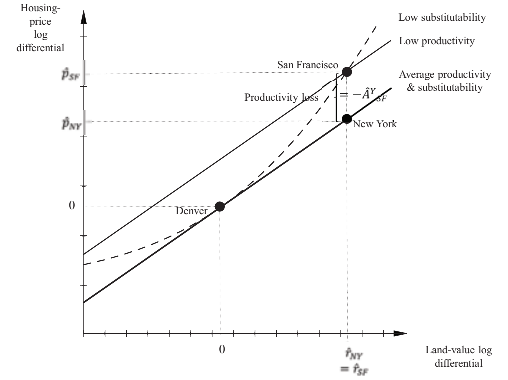


Figure 1C: Housing Prices vs. Land Values

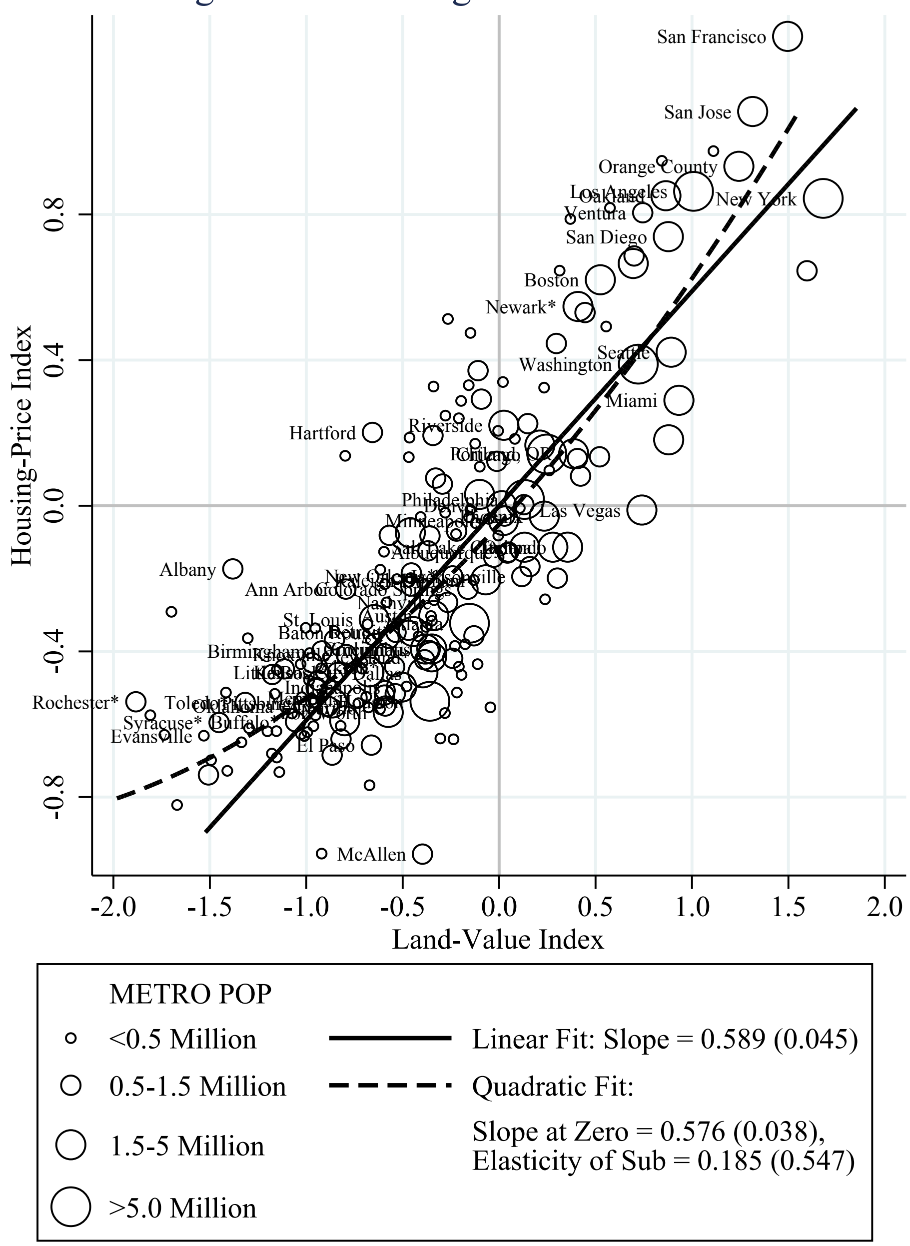


Figure 2: Land Sales in Selected Metro Areas

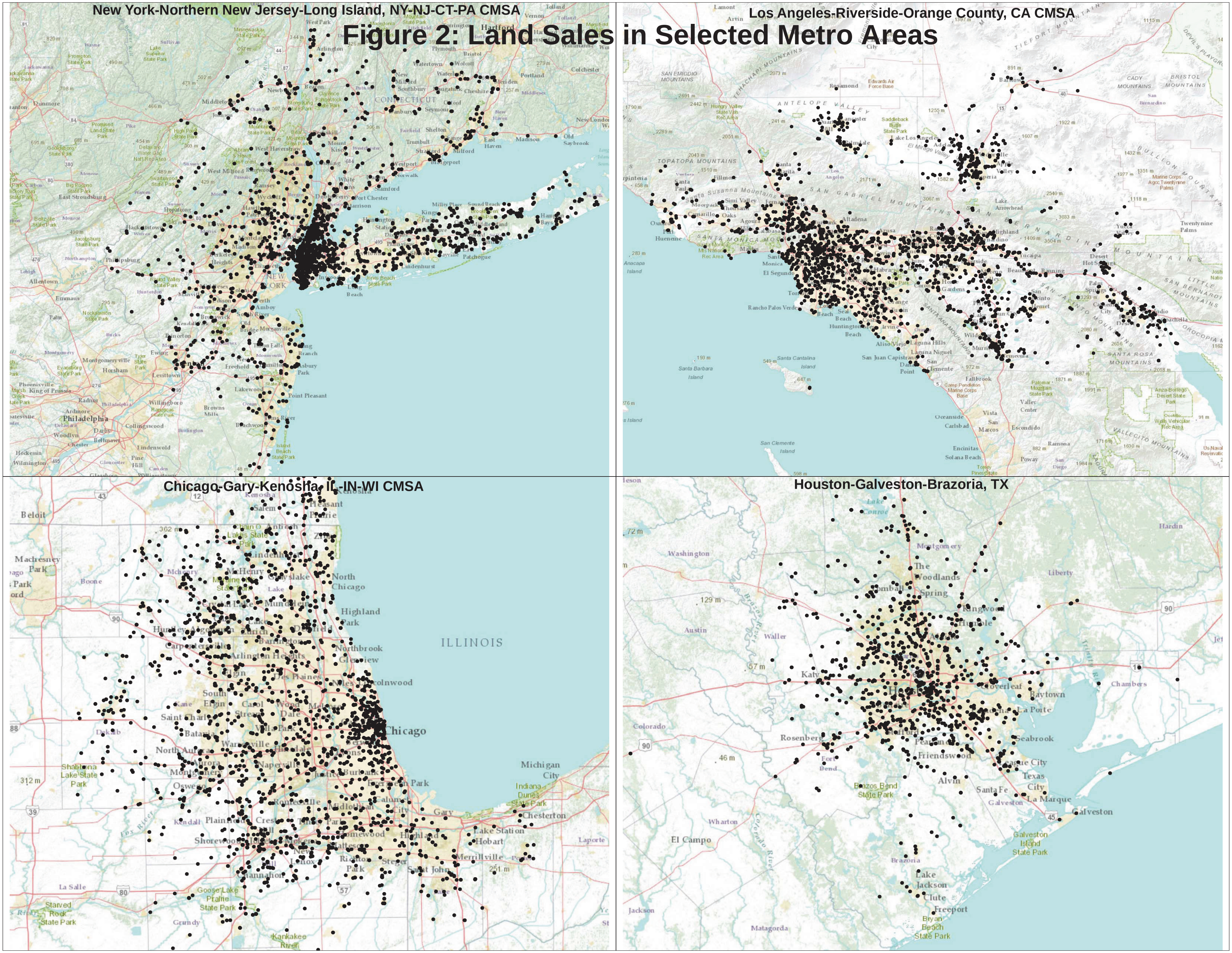


Figure 3A: Construction Prices vs. Land Values

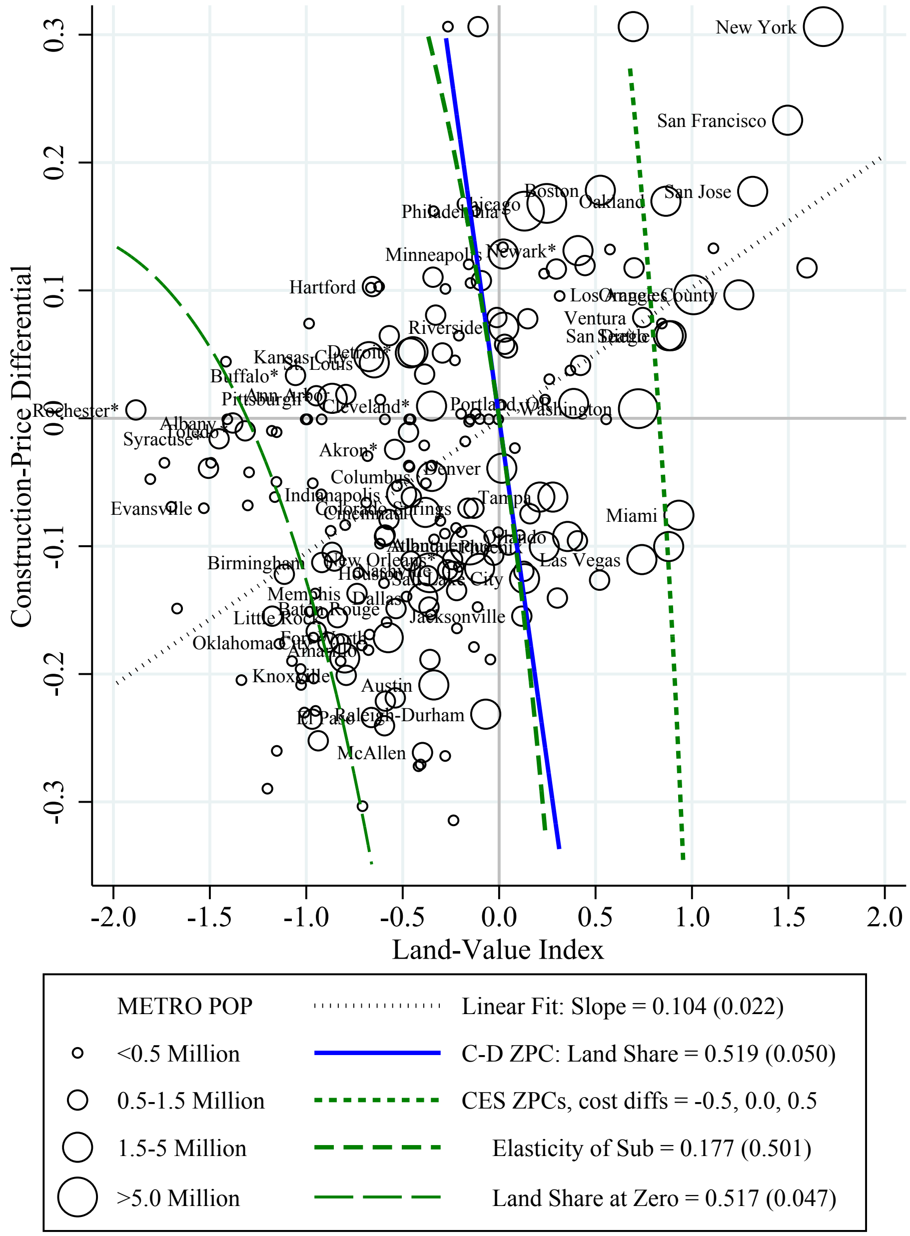


Figure 3B: Three-Dimensional Cost Curve, corresponding to ZPC
Curves in Figure 3A, Estimated from Data, No Covariates

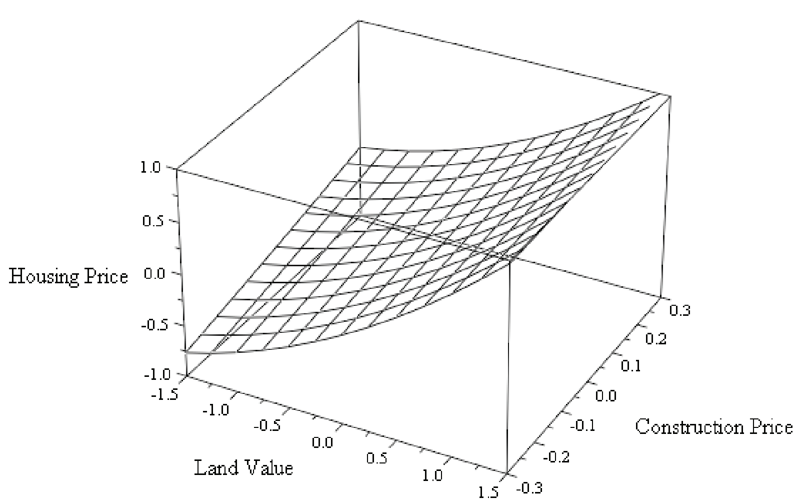


Fig. 4: Productivity in the Tradeable and Housing Sectors

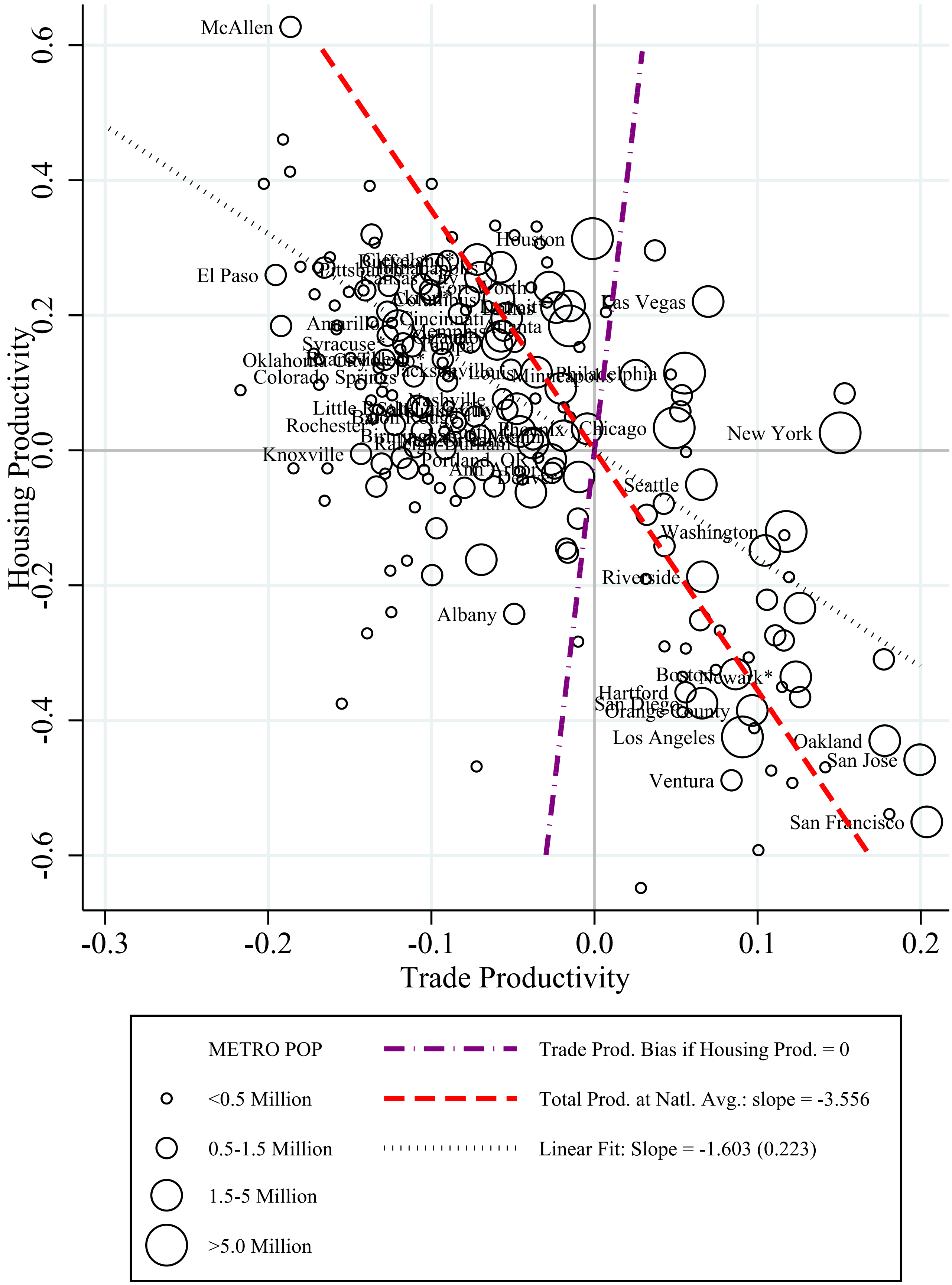
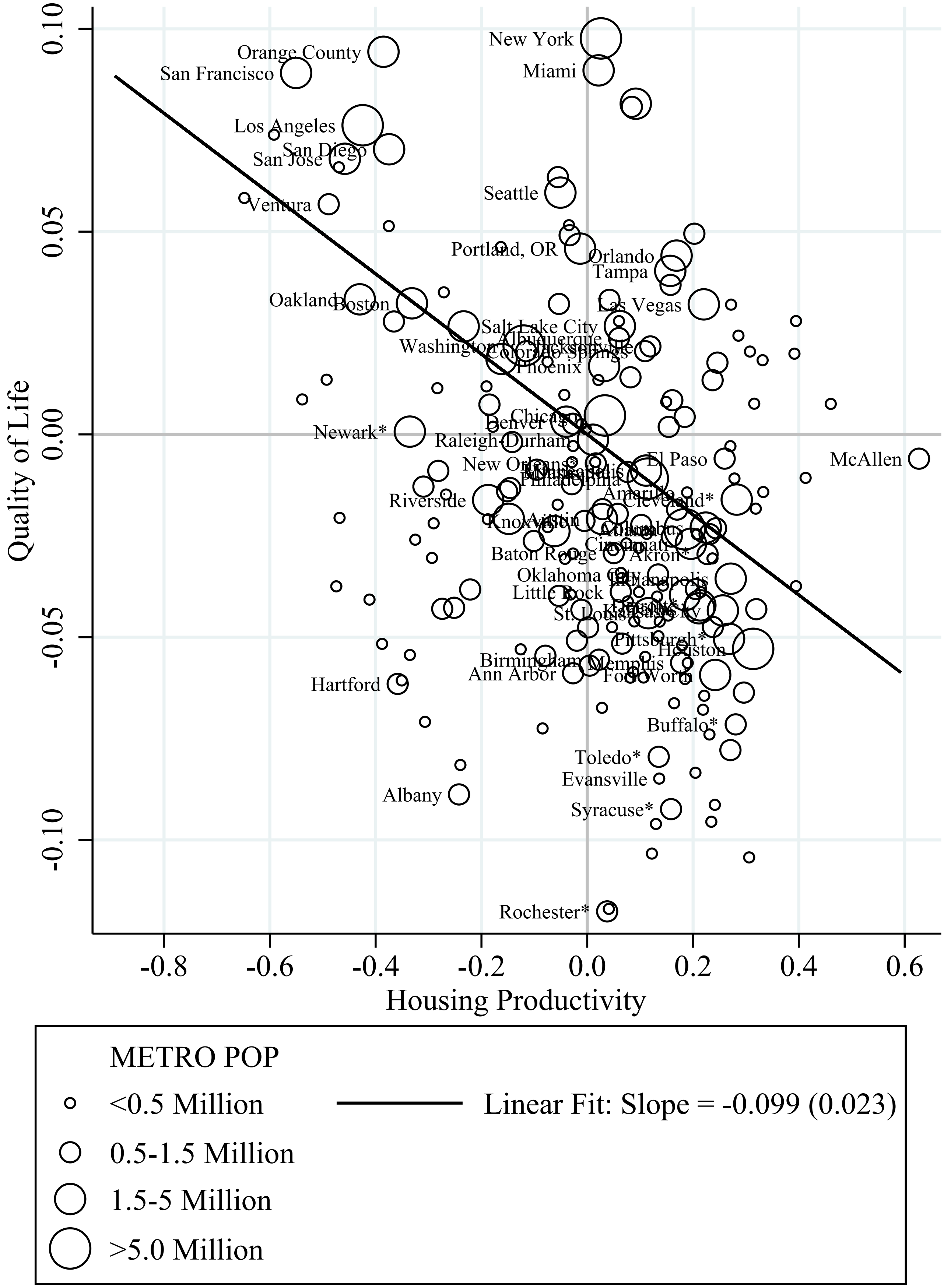


Figure 5: Quality of Life vs. Housing Productivity



Appendix for Online Publication Only

A Constructing the Land Values Sample

We use every sale CoStar deems to be "land" that occurred between 2005 and 2010 in a Metropolitan Statistical Area (MSA). We use the June 30, 1999 definitions provided by the Office of Management and Budget. The data are organized by Primary Metropolitan Statistical Areas (PMSAs) within larger Consolidated Metropolitan Statistical Areas (CMSAs). We exclude all transactions CoStar has marked as non-arms length or without complete information for lot size, sales price, county, and date, or that appear to feature a structure. Finally, we drop observations we could not geocode, leaving us with 68,757 observed land sales.[27]

To address the possible bias arising from the geographical distribution of observed land sales, we re-weight the observed sales to reflect the distribution of housing units within metro areas. For each MSA, we pinpoint the metropolitan center using Google Maps.[28] Then, we regress the log number of housing units per square mile at the census-tract level on the North-South and East-West distances between the tract center and the city center, and the squares and product of these distances. We calculate the predicted density of each observed land sale using the city-specific coefficients from this regression, and use this predicted density in column 4 of Table 1, which we take as our preferred measure. The unweighted and weighted indices are highly correlated (the correlation coefficient is above 0.99), although the latter are somewhat more dispersed, as expected.

Because our focus is on residential housing, it may be inappropriate to use land sales with non-residential proposed uses, especially if land markets are somehow segmented. Ultimately, we find that indices constructed only from land sales with a proposed residential use (i.e., single family, multi-family, or apartments) do not differ systematically from our preferred index, except that they are less precise. Figure A contrasts the differences between shrunken and unshrunken indices, figure B, between weighted and un-weighted indices, and figure C, between using all land and land only for residential uses. While there are some differences between these indices, their overall patterns are quite similar.

[27]We consider an observation to feature a structure when the transaction record includes the fields for "Bldg Type", "Year Built", "Age", or the phrase "Business Value Included" in the field "Sale Conditions." We geocoded using the Stata module "geocode" from Ozimek and Miles (2011). In addition, we drop outlier observations that we calculate as farther than 75 miles from the city center or that have a predicted density greater than 50,000 housing units per square mile using the weighting scheme described below. We also exclude outlier observations with a listed price of less than $100 per acre or a lot size over 5,000 acres.

[28]These centers are generally within a few blocks of the city hall of the MSA's central city.

B Factor-Specific Productivity Biases

When housing productivity is factor specific we may write the production function for housing as $Y_j = F^Y(L, M; A_j^Y) = F^Y(A_j^{YL}L, A_j^{YM}M; 1)$. The first-order log-linear approximation of the production function around the national average is

$$\hat{p}_j = \phi^L\hat{r}_j + (1-\phi^L)\hat{v}_j - [\phi^L\hat{A}_j^{YL} + (1-\phi^L)\hat{A}_j^{YM}]$$

As both $\hat{A}_j^{YL}$ and $\hat{A}_j^{YM}$ are only in the residual, it is difficult to identify them separately. The second-order log-linear approximation of the production function is

$$\begin{aligned}\hat{p}_j &= \phi^L(\hat{r}_j - \hat{A}_j^{YL}) + (1-\phi^L)(\hat{v}_j - \hat{A}_j^{YM}) + (1/2)\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{A}_j^{YL} - \hat{v}_j + \hat{A}_j^{YM})^2 \\ &= \phi^L\hat{r}_j + (1-\phi^L)\hat{v}_j + (1/2)\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{v}_j)^2 \\ &+ \phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{v}_j)(\hat{A}_j^{YM} - \hat{A}_j^{YL}) \\ &- [\phi^L\hat{A}_j^{YL} + (1-\phi^L)\hat{A}_j^{YM}] + (1/2)\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{A}_j^{YL} - \hat{A}_j^{YM})^2 \qquad \text{(A.1)}\end{aligned}$$

The terms on the second-to-last line demonstrate that if $\sigma^Y < 1$, then productivity improvements that affect land more will exhibit a negative interaction with the rent variable and a positive interaction with the material price, while productivity improvements that affect material use more, will exhibit the opposite effects. Therefore, if a productivity shifter Z_j biases productivity so that $(\hat{A}_j^{YM} - \hat{A}_j^{YL}) = Z_j\zeta$, we may identify factor-specific productivity biases with the following reduced-form equation:

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

The model embodied in (A.1) imposes the restriction that $\gamma_2 = -\gamma_3 = \zeta\phi^L(1-\phi^L)(1-\sigma^Y)$.

C 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:

- 12 indicators of educational attainment;

- a quartic in potential experience and potential experience interacted with years of education;
- age and age squared;
- 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.

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 2000-2007 occupation codes. In our sample, 4.5% of all workers are in the construction sector.

As noted in section 4.2, 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.[29]

[29]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, but in most cases the correspondence is clear. If an MSA contains more than one RS Means city we use the construction cost index of the city in the MSA that also has an entry in RS Means. If a PMSA is separately defined in RS Means we use the cost index for that PMSA; otherwise we use the cost index for the principal city of the parent CMSA. We only have the 2010 edition of the RS Means index.

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

- survey year dummies;
- 9 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;
- 3 indicators for lot size;
- 13 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 (owned units only).

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.

D Estimate Stability

We conduct several exercises to guage the stability of our estimates; the results of these exercises are reported in table A2. First, we split the sample into two periods: a“housing-boom” period, from 2005 to 2007, and a “housing-bust” period, from 2008 to 2010. As seen in columns 2 and 3, the regression results for the split samples are not statistically different from those in the pooled sample, in column 1. Comparing the two split samples, the latter period does have a somewhat lower elasticity of substitution, and weaker effects of geographic and regulatory constraints. Whether this is a product of sampling error or secular changes in housing production remains to be seen.

Second, we report results for the same regressions using three alternative land-value indices: i) residential land values only, ii) “raw” land-value indices, and iii) unshrunken land-value indicies. Land is defined as residential if its proposed use is listed as single-family, multi-family, or apartments. Raw land-value indices are procured by regressing log price per acre on a set of MSA indicators without any additional covariates, such as proposed use or lot size, and are not reweighted by location, corresponding to the regression in column 1 of table 1. The unshrunken indices are derived directly from the regression in column 4 of table 1, without applying the Kane and Staiger (2008) shrinkage technique. The results for the residential land values in column 4 are nearly identical to those in column 1. In columns 5 and 6, the estimated land share is lower as we see more dispersion in the land index, which causes attenuation: the first, from noise introduced by not having controls; the second, from sampling error.

The results in column 7 drop metro areas with population growth from 1980 to 2010 in the bottom decile, where the zero-profit condition may fail. The estimated cost share of land is similar and the elasticity of substitution using this sample is lower, albeit not significantly so. If we instead define our low-growth sample using the bottom decile of MSAs in terms of the building permits issued from 2005 to 2010 relative to the size of the housing stock, as in column 8, the results are close to our base specification.

TABLE A1: INSTRUMENTAL VARIABLES ESTIMATES, FIRST-STAGE REGRESSIONS

Dependent Variable	Land Rent minus Construction Price (1)	Land Rent minus Construction Price (2)	Land Rent minus Construction Price Squared (3)
Geographic Constraint Index: z-score	0.075	0.076	0.021
	(0.060)	(0.073)	(0.070)
Regulatory Index: z-score	0.108	0.113	-0.095
	(0.055)	(0.047)	(0.040)
Inverse of Mean Distance from Sea: z-score	0.280	0.242	-0.040
	(0.053)	(0.139)	(0.103)
Inverse of Mean Distance from Sea: z-score squared		0.015	0.099
		(0.047)	(0.028)
USDA Amenities Score: z-score	0.081	0.076	-0.039
	(0.022)	(0.028)	(0.029)
USDA Amenities Score: z-score squared		0.003	0.026
		(0.006)	(0.006)
Number of Observations	206	206	206
Adjusted R-squared	0.576	0.574	0.303
F-statistic of Excluded Instruments	15.2	8.9	39.2
p-value of test of Instrument Exogeneity	0.662	0.859	
First Stage Regression for	Table 3 Column 5	Table 3 Column 6	Table 3 Column 6

Robust standard errors, clustered by CMSA, in parentheses. Inverse of mean distance from sea and mean winter is from Albouy et al. (2012). USDA amenities score is the sum of the fist four components of the USDA Amenities Score (McGranahan 1999): mean January temperature, mean January hours of sunlight, mean July temperature, and mean July relative humidity. The fifth and sixth components are ommitted because they concern topological measures and water coverage similar to the measures that form the Geographic Constraint Index. Test of instrument exogeneity is from Sargan (1958).

TABLE A2: MODEL OF HOUSING COSTS, ROBUSTNESS ANALYSIS

Specification Dependent Variable	Base Specification Hous. Price (1)	2005-2007 Sample Hous. Price (2)	2008-2010 Sample Hous. Price (3)	Residential Land Sample Hous. Price (4)	Raw Land Values Hous. Price (5)	Unshrunken Land Values Hous. Price (6)	High Population Growth Sample Hous. Price (7)	High Building Permits Sample Hous. Price (8)
Land-Value Differential	0.376	0.366	0.383	0.384	0.245	0.286	0.344	0.363
	(0.036)	(0.040)	(0.037)	(0.039)	(0.028)	(0.033)	(0.037)	(0.038)
Construction-Price Differential	0.624	0.634	0.617	0.616	0.755	0.714	0.656	0.637
	(0.036)	(0.040)	(0.037)	(0.039)	(0.028)	(0.033)	(0.037)	(0.038)
Land-Value Differential Squared	0.076	0.054	0.099	0.068	-0.006	0.060	0.103	0.077
	(0.034)	(0.038)	(0.036)	(0.036)	(0.018)	(0.019)	(0.047)	(0.035)
Construction-Price Differential Squared	0.076	0.054	0.099	0.068	-0.006	0.060	0.103	0.077
	(0.034)	(0.038)	(0.036)	(0.036)	(0.018)	(0.019)	(0.047)	(0.035)
Land-Value Differential X Construction-Price Differential	-0.152	-0.108	-0.198	-0.136	0.012	-0.120	-0.206	-0.154
	(.068)	(.076)	(.072)	(.072)	(.036)	(.038)	(.094)	(.07)
Geographic Constraint Index: z-score	0.093	0.120	0.069	0.086	0.105	0.121	0.107	0.095
	(.027)	(.032)	(.024)	(.028)	(.029)	(.031)	(.029)	(.027)
Regulatory Index: z-score	0.075	0.092	0.064	0.076	0.095	0.088	0.076	0.077
	(.014)	(.016)	(.015)	(.016)	(.013)	(.014)	(.013)	(.014)
Number of Observations	856	338	518	680	856	856	756	772
Adjusted R-squared	0.745	0.734	0.764	0.743	0.727	0.734	0.727	0.732
Elasticity of Subsitution	0.349	0.537	0.159	0.429	1.062	0.417	0.089	0.338
	(0.278)	(0.314)	(0.288)	(0.295)	(0.192)	(0.161)	(0.396)	(0.290)

Robust standard errors, clustered by CMSA, reported in parentheses. Regressions correspond to column 4 of Table 3. See appendix D for discussion.

TABLE A3: LIST OF METROPOLITAN INDICES RANKED BY LAND PRICE DIFFERENTIAL, 2005-2010

				Adjusted Differentials					*Raw Differentials*			*Productivity*		
Full Name	Population	Census Division	Obs. Land Sales	Land Value	Land Value (No Wts.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Unavail. Index (z-score)	Const. Price Index	Housing	Tradeables	Land Value Rank
Metropolitan Areas:														
New York, NY PMSA	9,747,281	2	1,603	1.681	1.546	0.844	0.152	0.247	-0.221	0.561	0.306	0.026	0.151	1
Jersey City, NJ PMSA	597,924	2	43	1.596	1.457	0.645	0.159	0.262	-0.594	0.236	0.118	0.084	0.153	2
San Francisco, CA PMSA	1,785,097	9	152	1.496	1.416	1.289	0.207	0.214	1.684	2.169	0.233	-0.550	0.204	3
San Jose, CA PMSA	1,784,642	9	217	1.315	1.273	1.083	0.207	0.214	-0.107	1.710	0.177	-0.458	0.199	4
Orange County, CA PMSA	3,026,786	9	233	1.243	1.192	0.932	0.087	0.115	0.026	1.153	0.097	-0.385	0.097	5
Stamford-Norwalk, CT PMSA	361,024	1	19	1.111	1.020	0.974	0.157	0.243	-0.624	0.561	0.133	-0.469	0.141	6
Los Angeles-Long Beach, CA PMSA	9,848,011	9	1,760	1.008	0.961	0.863	0.087	0.115	0.841	1.153	0.097	-0.424	0.091	7
Miami, FL PMSA	2,500,625	5	1,233	0.932	0.909	0.289	-0.057	-0.081	0.662	2.341	-0.076	0.021	-0.019	8
Seattle-Bellevue-Everett, WA PMSA	2,692,066	9	1,626	0.892	0.848	0.422	0.051	0.035	1.642	0.719	0.065	-0.051	0.065	9
Fort Lauderdale, FL PMSA	1,766,476	5	741	0.879	0.863	0.181	-0.057	-0.082	0.890	2.295	-0.100	0.092	-0.021	10
San Diego, CA MSA	3,053,793	9	957	0.877	0.878	0.739	0.061	0.093	0.946	1.691	0.065	-0.375	0.066	11
Oakland, CA PMSA	2,532,756	9	132	0.865	0.781	0.851	0.192	0.186	0.543	1.605	0.170	-0.430	0.178	12
Santa Barbara-Santa Maria-Lompoc, CA MSA	407,057	9	29	0.844	0.746	0.947	0.073	-0.066	0.542	2.802	0.074	-0.592	0.100	13
Ventura, CA PMSA	802,983	9	131	0.745	0.757	0.805	0.086	0.115	1.668	2.489	0.079	-0.489	0.084	14
Las Vegas, NV-AZ MSA	2,141,893	8	2,553	0.740	0.756	-0.012	0.044	-0.063	-1.524	0.150	-0.110	0.220	0.070	15
Washington, DC-MD-VA-WV PMSA	5,650,154	5	1,840	0.722	0.728	0.389	0.132	0.177	0.850	-0.741	0.008	-0.120	0.117	16
Bergen-Passaic, NJ PMSA	1,387,028	2	79	0.700	0.652	0.686	0.152	0.247	0.317	0.561	0.118	-0.366	0.126	17
Nassau-Suffolk, NY PMSA	2,875,904	2	396	0.695	0.663	0.665	0.152	0.247	0.811	0.561	0.306	-0.234	0.126	18
Santa Rosa, CA PMSA	472,102	9	153	0.575	0.584	0.818	0.207	0.214	1.285	1.671	0.132	-0.539	0.181	19
Naples, FL MSA	318,537	5	78	0.555	0.572	0.492	0.008	-0.213	0.125	2.291	-0.001		0.052	20
Boston, MA-NH PMSA	3,552,421	1	122	0.525	0.497	0.621	0.093	0.101	1.264	0.241	0.178	-0.331	0.087	21
West Palm Beach-Boca Raton, FL MSA	1,279,950	5	321	0.521	0.419	0.134	-0.033	0.046	0.309	1.720	-0.127	-0.033	-0.026	22
Vallejo-Fairfield-Napa, CA PMSA	541,884	9	146	0.445	0.465	0.531	0.207	0.214	0.853	0.990	0.119	-0.310	0.177	23
Tacoma, WA PMSA	796,836	9	539	0.422	0.414	0.081	0.050	0.033	-0.214	0.377	0.041	0.082	0.054	24
Newark, NJ PMSA	2,045,344	2	142	0.409	0.357	0.547	0.159	0.262	0.005	0.073	0.131	-0.335	0.123	25
Sarasota-Bradenton, FL MSA	688,126	5	601	0.406	0.420	0.130	-0.103	-0.061	1.529	1.849	-0.096	-0.056	-0.080	26
Portland-Vancouver, OR-WA PMSA	2,230,947	9	1,191	0.386	0.361	0.143	-0.049	-0.071	-0.038	0.419	0.012	-0.014	-0.027	27
San Luis Obispo-Atascadero-Paso Robles, CA MSA	266,971	9	43	0.369	0.267	0.787	0.003	-0.112	1.399	1.810	0.037	-0.648	0.028	28
Orlando, FL MSA	2,082,421	5	1,612	0.355	0.382	-0.114	-0.088	-0.121	0.079	0.350	-0.092	0.169	-0.057	29
Salinas, CA MSA	410,370	9	12	0.314	0.238	0.646	0.113	-0.035	-0.074	1.824	0.096	-0.493	0.121	30
Provo-Orem, UT MSA	545,307	8	47	0.302	0.265	-0.199	-0.128	-0.217	-0.573	1.503	-0.141	0.202	-0.083	31
Middlesex-Somerset-Hunterdon, NJ PMSA	1,247,641	2	101	0.297	0.277	0.446	0.152	0.247	2.182	0.561	0.117	-0.282	0.116	32
Tampa-St. Petersburg-Clearwater, FL MSA	2,747,272	5	1,220	0.278	0.288	-0.114	-0.091	-0.140	-0.050	0.621	-0.062	0.157	-0.060	33
Olympia, WA PMSA	250,979	9	250	0.260	0.245	0.097	0.060	0.054	0.626	0.466	0.031	-0.003	0.056	34
Chicago, IL PMSA	8,710,824	3	3,511	0.247	0.259	0.142	0.054	0.058	-0.603	0.541	0.168	0.033	0.049	35
Reading, PA MSA	407,125	2	36	0.238	0.246	-0.257	-0.050	-0.046	0.658	-0.616	0.015	0.331	-0.036	36
Phoenix-Mesa, AZ MSA	4,364,094	8	5,946	0.234	0.296	-0.028	-0.013	-0.014	0.962	-0.741	-0.100	0.032	-0.004	37
Trenton, NJ PMSA	366,222	2	35	0.233	0.258	0.324	0.159	0.262	1.712	-0.847	0.113	-0.188	0.119	38
Baltimore, MD PMSA	2,690,886	5	802	0.211	0.212	0.167	0.131	0.177	-0.661	-0.351	-0.062	-0.148	0.104	39
Melbourne-Titusville-Palm Bay, FL MSA	536,357	5	420	0.160	0.189	-0.167	-0.112	-0.065	0.352	1.732	-0.075	0.157	-0.094	40
Stockton-Lodi, CA MSA	674,860	9	163	0.148	0.128	0.226	0.067	0.165	0.099	-0.834	0.078	-0.142	0.043	41
Salt Lake City-Ogden, UT MSA	1,567,650	8	145	0.132	0.104	-0.114	-0.078	-0.159	-0.509	2.113	-0.125	0.062	-0.048	42
Philadelphia, PA-NJ PMSA	5,332,822	2	859	0.132	0.146	0.017	0.062	0.045	0.644	-0.927	0.162	0.114	0.055	43
Fort Myers-Cape Coral, FL MSA	586,908	5	294	0.128	0.140	0.003	-0.078	-0.071	-0.553	1.187	-0.120	-0.054	-0.062	44
Jacksonville, FL MSA	1,301,808	5	793	0.118	0.139	-0.194	-0.076	-0.130	0.702	0.900	-0.155	0.119	-0.051	45
Grand Junction, CO MSA	146,093	8	21	0.107	0.045	-0.006	-0.146	-0.060	0.457	0.702	-0.091	-0.035	-0.128	46
Reno, NV MSA	414,820	8	57	0.082	0.087	0.184	0.003	-0.178	-0.486	1.328	-0.023	-0.190	0.031	47
Albuquerque, NM MSA	841,428	8	114	0.049	0.020	-0.127	-0.087	-0.195	0.957	-0.854	-0.099	0.060	-0.053	48
Allentown-Bethlehem-Easton, PA MSA	706,374	2	85	0.043	0.037	-0.130	-0.040	0.079	0.412	-0.401	0.055	0.161	-0.049	49
Wilmington-Newark, DE-MD PMSA	635,430	5	107	0.028	0.051	-0.028	0.062	0.045	0.706	-0.705	0.058	0.058	0.053	50
Riverside-San Bernardino, CA PMSA	4,143,113	9	2,452	0.024	0.054	0.221	0.087	0.115	0.599	0.437	0.071	-0.187	0.066	51
Minneapolis-St. Paul, MN-WI MSA	3,269,814	4	846	0.022	0.012	-0.041	0.024	-0.011	0.104	-0.481	0.128	0.111	0.025	52
Lawrence, MA-NH PMSA	413,626	1	29	0.020	-0.028	0.340	0.099	0.121	1.811	0.241	0.134	-0.267	0.077	53
Denver, CO PMSA	2,445,781	8	2,015	0.014	0.000	0.000	-0.010	0.003	1.299	-0.604	-0.039	-0.039	-0.010	54
Kenosha, WI PMSA	165,382	3	58	0.009	0.041	-0.123	0.059	0.068	1.833	0.929	0.011	0.112	0.047	55
Fort Pierce-Port St. Lucie, FL MSA	406,296	5	71	-0.004	-0.017	-0.082	-0.075	-0.191	0.298	1.765	-0.001		-0.044	56
Boulder-Longmont, CO PMSA	311,786	8	183	-0.005	0.001	0.206	-0.010	0.003	4.034	0.695	-0.089	-0.283	-0.010	57
Modesto, CA MSA	510,385	9	142	-0.012	-0.028	0.122	0.041	0.044	-0.211	-0.724	0.079	-0.095	0.032	58
Daytona Beach, FL MSA	587,512	5	93	-0.028	-0.022	-0.141	-0.135	-0.303	-0.845	1.549	-0.107	0.042	-0.085	59
Sioux Falls, SD MSA	224,266	4	17	-0.045	-0.146	-0.554	-0.182	0.181	-1.485	-1.260	-0.189	0.395	-0.203	60

TABLE A3: LIST OF METROPOLITAN INDICES RANKED BY LAND PRICE DIFFERENTIAL, 2005-2010

				Adjusted Differentials					*Raw Differentials*			*Productivity*		
Full Name	Population	Census Division	Obs. Land Sales	Land Value	Land Value (No Wts.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Unavail. Index (z-score)	Const. Price Index	Housing	Tradeables	Land Value Rank
Visalia-Tulare-Porterville, CA MSA	429,668	9	32	-0.053	-0.162	-0.036	-0.016	-0.019	0.322	-0.471	-0.001		-0.014	61
Raleigh-Durham-Chapel Hill, NC MSA	1,589,388	5	782	-0.069	-0.060	-0.203	-0.042	-0.033	1.107	-1.027	-0.231	0.011	-0.038	62
New Haven-Meriden, CT PMSA	558,692	1	43	-0.092	-0.135	0.293	0.159	0.262	-0.636	0.786	0.108	-0.274	0.111	63
Eugene-Springfield, OR MSA	351,109	9	36	-0.100	-0.173	0.107	-0.154	-0.239	0.152	1.647	-0.001	-0.163	-0.115	64
Norfolk-Virginia Beach-Newport News, VA- MSA	1,667,410	5	392	-0.101	-0.092	0.031	-0.078	-0.053	-0.222	1.512	-0.117	-0.162	-0.069	65
Monmouth-Ocean, NJ PMSA	1,217,783	2	124	-0.109	-0.122	0.371	0.152	0.247	2.067	0.561	0.306	-0.221	0.106	66
Huntsville, AL MSA	406,316	6	29	-0.112	-0.115	-0.435	-0.055	-0.177	-2.387	-0.230	-0.148	0.278	-0.029	67
Salem, OR PMSA	396,103	9	54	-0.122	-0.182	-0.048	-0.042	-0.063	0.580	0.199	0.003	-0.011	-0.034	68
Newburgh, NY-PA PMSA	444,061	2	54	-0.124	-0.120	0.170	0.166	0.265	-0.538	0.047	0.162	-0.126	0.116	69
Lakeland-Winter Haven, FL MSA	583,403	5	561	-0.130	-0.080	-0.357	-0.138	-0.201	0.337	0.156	-0.070	0.246	-0.106	70
Savannah, GA MSA	343,092	5	64	-0.131	-0.144	-0.204	-0.102	-0.168	-0.280	1.528	-0.179	0.021	-0.076	71
Bridgeport, CT PMSA	470,094	1	26	-0.149	-0.253	0.475	0.157	0.254	0.304	0.561	0.106	-0.474	0.108	72
Merced, CA MSA	245,321	9	64	-0.149	-0.139	-0.011	-0.005	0.255	0.603	-0.927	-0.001		-0.046	73
Atlanta, GA MSA	5,315,841	5	5,229	-0.154	-0.113	-0.323	-0.007	0.033	0.028	-1.225	-0.099	0.184	-0.015	74
Madison, WI MSA	491,357	3	239	-0.156	-0.150	-0.032	-0.070	-0.180	0.326	-0.869	-0.003	-0.043	-0.044	75
Brockton, MA PMSA	268,092	1	22	-0.158	-0.170	0.331	0.097	0.096	2.833	0.241	0.120	-0.325	0.074	76
Colorado Springs, CO MSA	604,542	8	892	-0.162	-0.198	-0.229	-0.134	-0.150	0.239	-0.331	-0.070	0.109	-0.111	77
Janesville-Beloit, WI MSA	160,155	3	15	-0.176	-0.255	-0.380	-0.172	-0.046	-0.764	-1.190	-0.018	0.286	-0.162	78
Hamilton-Middletown, OH PMSA	363,184	3	151	-0.195	-0.172	-0.465	-0.052	-0.040	-0.641	-1.083	-0.089	0.318	-0.049	79
Medford-Ashland, OR MSA	201,286	9	12	-0.197	-0.338	0.288	-0.164	-0.046	0.874	2.003	0.003	-0.375	-0.155	80
Lincoln, NE MSA	281,531	4	24	-0.209	-0.264	-0.442	-0.212	-0.189	0.750	-1.348	-0.116	0.272	-0.180	81
Bremerton, WA PMSA	240,862	9	18	-0.209	-0.249	0.240	0.060	0.063	0.026	1.124	0.065	-0.290	0.043	82
Fargo-Moorhead, ND-MN MSA	200,102	4	13	-0.219	-0.378	-0.513	-0.188	-0.340	-2.158	-1.281	-0.164	0.307	-0.135	83
Tucson, AZ MSA	1,020,200	8	1,749	-0.220	-0.230	-0.070	-0.123	-0.178	0.200	-0.292	-0.135	-0.115	-0.097	84
Fort Collins-Loveland, CO MSA	298,382	8	344	-0.223	-0.216	-0.078	-0.116	-0.216	0.831	0.110	-0.086	-0.075	-0.085	85
Champaign-Urbana, IL MSA	195,671	3	22	-0.229	-0.273	-0.385	-0.130	-0.289	-0.900	-1.355	0.045	0.316	-0.087	86
Rocky Mount, NC MSA	146,596	5	12	-0.236	-0.382	-0.641	-0.100	-0.275	-0.921	-0.519	-0.314	0.333	-0.061	87
Lexington, KY MSA	554,107	6	29	-0.241	-0.303	-0.419	-0.156	-0.100	-0.153	-1.136	-0.120	0.237	-0.141	88
New Orleans, LA MSA*	1,211,035	7	66	-0.241	-0.292	-0.193	-0.057	-0.156	-2.433	2.255	-0.110	0.016	-0.038	89
Danbury, CT PMSA	223,095	1	23	-0.266	-0.336	0.513	0.149	0.255	-0.586	0.561	0.306	-0.412	0.098	90
Nashville, TN MSA	1,495,419	6	455	-0.267	-0.252	-0.265	-0.066	-0.095	-1.132	-0.795	-0.119	0.076	-0.056	91
Atlantic-Cape May, NJ PMSA	367,803	2	37	-0.278	-0.307	0.248	0.074	0.055	0.284	1.778	0.101	-0.294	0.056	92
Asheville, NC MSA	251,894	5	41	-0.280	-0.302	-0.019	-0.174	-0.229	0.097	1.891	-0.264	-0.271	-0.139	93
Lafayette, IN MSA	202,331	3	13	-0.281	-0.297	-0.569	-0.207	-0.454	-1.015	-0.147	-0.090	0.392	-0.138	94
Springfield, MA MSA*	609,993	1	28	-0.294	-0.362	0.060	-0.011	-0.007	0.056	-0.095	0.051	-0.146	-0.017	95
South Bend, IN MSA*	267,613	3	12	-0.305	-0.410	-0.639	-0.182	0.057	-2.105	-0.907	-0.080	0.460	-0.191	96
Fresno, CA MSA	1,063,899	9	137	-0.329	-0.304	0.076	-0.013	-0.034	1.181	-0.793	0.081	-0.151	-0.016	97
Billings, MT MSA	144,797	8	25	-0.337	-0.383	-0.259	-0.198	-0.441	-0.616	-0.868	-0.095	0.060	-0.133	98
Austin-San Marcos, TX MSA	1,705,075	7	384	-0.339	-0.295	-0.302	-0.049	-0.069	1.035	-1.241	-0.209	0.028	-0.046	99
Dutchess County, NY PMSA	293,562	2	33	-0.340	-0.304	0.327	0.170	0.262	0.169	0.561	0.162	-0.351	0.115	100
Worcester, MA-CT PMSA	547,274	1	56	-0.343	-0.359	0.193	0.093	0.101	2.406	0.241	0.110	-0.252	0.065	101
Columbus, OH MSA	1,718,303	3	671	-0.349	-0.319	-0.393	-0.058	-0.040	0.165	-1.303	-0.045	0.224	-0.059	102
Richland-Kennewick-Pasco, WA MSA	245,649	9	27	-0.349	-0.397	-0.316	0.022	0.146	0.789	-0.823	-0.037	0.153	-0.009	103
Cleveland-Lorain-Elyria, OH PMSA*	2,192,053	3	416	-0.350	-0.340	-0.415	-0.084	-0.115	-0.765	0.565	0.010	0.283	-0.072	104
Greeley, CO PMSA	254,759	8	320	-0.353	-0.303	-0.303	-0.010	0.002	-0.696	-0.930	-0.154	0.064	-0.019	105
Charleston-North Charleston, SC MSA	659,191	5	214	-0.359	-0.352	-0.083	-0.111	-0.107	-1.255	1.545	-0.189	-0.185	-0.100	106
Houston, TX PMSA	5,219,317	7	1,143	-0.359	-0.336	-0.537	0.014	0.036	-0.124	-1.013	-0.121	0.314	-0.001	107
Chattanooga, TN-GA MSA	510,388	6	51	-0.364	-0.373	-0.397	-0.141	-0.219	-1.395	-0.157	-0.148	0.154	-0.112	108
Richmond-Petersburg, VA MSA	1,119,459	5	399	-0.369	-0.354	-0.124	-0.012	-0.072	-0.859	-0.993	-0.123	-0.101	-0.010	109
La Crosse, WI-MN MSA	132,923	3	21	-0.380	-0.435	-0.333	-0.154	-0.258	-0.464	0.333	-0.051	0.149	-0.119	110
Cincinnati, OH-KY-IN PMSA	1,776,911	3	637	-0.383	-0.366	-0.394	-0.052	-0.040	-1.092	-0.920	-0.074	0.196	-0.054	111
Gary, IN PMSA	657,809	3	111	-0.386	-0.412	-0.423	0.060	0.068	-1.469	0.124	0.035	0.296	0.037	112
York, PA MSA	428,937	2	47	-0.388	-0.383	-0.215	-0.022	-0.107	0.836	-0.831	-0.021	0.049	-0.015	113
Dallas, TX PMSA	4,399,895	7	811	-0.395	-0.381	-0.459	-0.014	0.000	-0.728	-0.976	-0.141	0.211	-0.023	114
McAllen-Edinburg-Mission, TX MSA	741,152	7	61	-0.398	-0.409	-0.957	-0.205	-0.136	-0.795	-1.380	-0.261	0.627	-0.186	115
Hagerstown, MD PMSA	145,910	5	28	-0.407	-0.403	-0.031	0.136	0.171	0.137	-0.505	-0.271	-0.307	0.094	116
Fayetteville-Springdale-Rogers, AR MSA	425,685	7	43	-0.418	-0.410	-0.359	-0.118	-0.152	-0.688	-0.004	-0.272	0.015	-0.101	117
Detroit, MI PMSA*	4,373,040	3	679	-0.447	-0.442	-0.345	-0.010	-0.037	-0.309	-0.221	0.052	0.214	-0.015	118
Lancaster, PA MSA	507,766	2	57	-0.455	-0.451	-0.185	-0.083	-0.154	0.030	-0.841	-0.062	-0.029	-0.068	119
Boise City, ID MSA	571,271	8	106	-0.458	-0.461	-0.220	-0.136	-0.186	-1.095	0.361	-0.112	-0.027	-0.114	120
Fort Walton Beach, FL MSA	178,473	5	14	-0.459	-0.595	-0.199	-0.152	0.283	-0.523	1.457	-0.001		-0.200	121
Milwaukee-Waukesha, WI PMSA	1,559,667	3	399	-0.460	-0.445	-0.074	-0.031	-0.015	-0.514	0.628	0.051	-0.062	-0.039	122

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				Adjusted Differentials					*Raw Differentials*			*Productivity*		
Full Name	Population	Census Division	Obs. Land Sales	Land Value	Land Value (No Wts.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Unavail. Index (z-score)	Const. Price Index	Housing	Tradeables	Land Value Rank
Portsmouth-Rochester, NH-ME PMSA	262,128	1	13	-0.465	-0.545	0.187	0.095	0.171	0.994	0.241	-0.038	-0.388	0.054	123
Myrtle Beach, SC MSA	263,868	5	84	-0.466	-0.493	-0.209	-0.185	-0.128	-1.005	1.614	-0.001		-0.170	124
Manchester, NH PMSA	212,326	1	23	-0.468	-0.537	0.134	0.095	0.171	2.615	0.241	-0.037	-0.335	0.054	125
Harrisburg-Lebanon-Carlisle, PA MSA	667,425	2	89	-0.470	-0.451	-0.342	-0.068	-0.006	0.597	-0.245	-0.011	0.160	-0.076	126
Galveston-Texas City, TX PMSA	286,814	7	39	-0.480	-0.498	-0.496	0.032	0.063	0.349	2.266	-0.139	0.221	0.009	127
Indianapolis, IN MSA	1,823,690	3	193	-0.506	-0.514	-0.498	-0.065	-0.119	-1.804	-1.355	-0.059	0.271	-0.058	128
Spokane, WA MSA	468,684	9	55	-0.530	-0.578	-0.202	-0.118	-0.148	0.755	-0.082	-0.053	-0.029	-0.104	129
Baton Rouge, LA MSA	685,419	7	99	-0.535	-0.548	-0.348	-0.069	-0.044	-1.582	0.222	-0.149	0.050	-0.073	130
Tulsa, OK MSA	873,304	7	245	-0.539	-0.527	-0.516	-0.129	-0.069	-1.737	-1.117	-0.219	0.170	-0.127	131
Akron, OH PMSA*	699,935	3	169	-0.542	-0.523	-0.442	-0.084	-0.114	-0.080	-1.109	-0.024	0.227	-0.077	132
Bakersfield, CA MSA	807,407	9	64	-0.570	-0.604	-0.081	0.044	-0.102	-0.373	-0.236	0.065	-0.079	0.042	133
Louisville, KY-IN MSA	1,099,588	6	126	-0.571	-0.592	-0.364	-0.101	-0.141	-1.193	-0.802	-0.079	0.102	-0.090	134
Fort Worth-Arlington, TX PMSA	2,113,278	7	506	-0.575	-0.572	-0.568	-0.014	0.000	-0.478	-1.185	-0.172	0.242	-0.028	135
Roanoke, VA MSA	243,506	5	23	-0.584	-0.641	-0.265	-0.105	-0.138	-1.335	0.513	-0.160	-0.056	-0.095	136
Johnson City-Kingsport-Bristol, TN-VA MSA	503,010	6	28	-0.590	-0.634	-0.550	-0.217	-0.206	-1.569	1.292	-0.221	0.184	-0.192	137
Dayton-Springfield, OH MSA*	933,312	3	116	-0.591	-0.613	-0.508	-0.119	-0.193	-1.553	-1.375	-0.091	0.231	-0.100	138
Yuba City, CA MSA	165,539	9	13	-0.592	-0.735	-0.215	0.012	-0.066	-0.769	-0.743	-0.001		0.006	139
Greensboro--Winston Salem--High Point, NC MSA	1,416,374	5	438	-0.594	-0.590	-0.406	-0.124	-0.190	-0.815	-1.273	-0.240	0.029	-0.106	140
Omaha, NE-IA MSA	799,130	4	118	-0.595	-0.618	-0.520	-0.126	-0.065	-0.492	-1.262	-0.092	0.243	-0.126	141
Gainesville, FL MSA	243,574	5	34	-0.597	-0.637	-0.126	-0.148	-0.215	-0.237	-0.669	-0.129	-0.178	-0.125	142
Racine, WI PMSA	200,601	3	80	-0.616	-0.597	-0.176	-0.028	0.024	-1.338	1.233	0.015	-0.031	-0.046	143
Springfield, MO MSA	383,637	4	43	-0.618	-0.643	-0.559	-0.201	-0.260	-1.394	-1.100	-0.098	0.271	-0.169	144
Rockford, IL MSA	409,058	3	104	-0.622	-0.564	-0.542	-0.089	-0.011	-1.104	-1.319	0.103	0.395	-0.100	145
St. Louis, MO-IL MSA	2,733,694	4	364	-0.648	-0.638	-0.312	-0.039	-0.126	-1.636	-0.881	0.043	0.116	-0.036	146
Hartford, CT MSA	1,231,125	1	101	-0.657	-0.664	0.201	0.090	0.091	0.293	-0.281	0.103	-0.358	0.056	147
El Paso, TX MSA	751,296	7	94	-0.662	-0.699	-0.657	-0.215	-0.182	0.350	-1.174	-0.234	0.260	-0.195	148
St. Cloud, MN MSA	189,148	4	17	-0.665	-0.818	-0.368	-0.113	-0.313	-0.463	-0.414	0.102	0.207	-0.079	149
Bismarck, ND MSA	106,286	4	22	-0.672	-0.797	-0.768	-0.218	-0.262	-0.505	-1.138	-0.169	0.413	-0.187	150
Kansas City, MO-KS MSA	2,005,888	4	477	-0.675	-0.657	-0.456	-0.068	-0.086	-1.452	-1.140	0.048	0.256	-0.070	151
Amarillo, TX MSA	238,299	7	27	-0.677	-0.749	-0.554	-0.176	-0.414	-0.910	-1.254	-0.181	0.189	-0.124	152
Green Bay, WI MSA	247,319	3	49	-0.683	-0.700	-0.325	-0.076	-0.005	-0.477	-0.282	-0.030	0.065	-0.089	153
Canton-Massillon, OH MSA*	408,005	3	40	-0.689	-0.735	-0.524	-0.122	0.048	-1.172	-0.808	-0.066	0.237	-0.142	154
Hickory-Morganton-Lenoir, NC MSA	365,364	5	88	-0.708	-0.687	-0.431	-0.201	-0.171	-0.979	-0.395	-0.303	-0.027	-0.185	155
Biloxi-Gulfport-Pascagoula, MS MSA	355,075	6	30	-0.712	-0.779	-0.447	-0.127	-0.019	-1.198	1.134	-0.178	0.074	-0.137	156
Brazoria, TX PMSA	309,208	7	62	-0.730	-0.730	-0.542	0.035	0.056	-0.871	-1.013	-0.121	0.205	0.007	157
Memphis, TN-AR-MS MSA	1,230,253	6	173	-0.737	-0.726	-0.527	-0.050	-0.075	1.490	-0.827	-0.137	0.177	-0.056	158
Knoxville, TN MSA	785,490	6	193	-0.793	-0.779	-0.409	-0.156	-0.175	-0.928	0.468	-0.201	-0.005	-0.143	159
Ann Arbor, MI PMSA*	630,518	3	136	-0.795	-0.762	-0.229	-0.010	-0.036	1.235	-0.949	0.019	-0.027	-0.024	160
Portland, ME MSA	256,178	1	25	-0.798	-0.881	0.137	-0.079	-0.156	0.846	1.005	-0.084	-0.468	-0.072	161
San Antonio, TX MSA	1,928,154	7	348	-0.801	-0.800	-0.590	-0.126	-0.136	1.707	-1.270	-0.187	0.185	-0.120	162
Wichita, KS MSA	589,195	4	54	-0.820	-0.889	-0.641	-0.112	-0.183	-1.987	-1.345	-0.176	0.237	-0.101	163
Lake Charles, LA MSA	187,554	7	14	-0.822	-0.925	-0.605	-0.079	0.268	-2.005	0.980	-0.190	0.190	-0.136	164
Little Rock-North Little Rock, AR MSA	657,416	7	110	-0.838	-0.849	-0.458	-0.116	-0.181	-1.894	-0.752	-0.156	0.063	-0.106	165
Des Moines, IA MSA	536,664	4	99	-0.854	-0.855	-0.368	-0.079	-0.036	-1.546	-1.123	-0.112	0.002	-0.091	166
Pittsburgh, PA MSA*	2,287,106	2	240	-0.866	-0.844	-0.542	-0.097	-0.118	-0.131	0.050	0.016	0.268	-0.098	167
Fort Wayne, IN MSA	528,408	3	39	-0.866	-0.871	-0.685	-0.142	-0.142	-1.612	-1.300	-0.105	0.320	-0.137	168
Cedar Rapids, IA MSA	209,226	4	33	-0.874	-0.946	-0.488	-0.124	-0.159	-1.435	-1.252	-0.088	0.132	-0.118	169
Oklahoma City, OK MSA	1,213,704	7	395	-0.887	-0.905	-0.550	-0.154	-0.276	-1.133	-1.305	-0.175	0.134	-0.129	170
Jackson, MS MSA	483,852	6	43	-0.916	-0.940	-0.523	-0.091	-0.138	-2.341	-0.869	-0.152	0.110	-0.090	171
Birmingham, AL MSA	997,770	6	148	-0.920	-0.943	-0.399	-0.071	-0.141	-0.476	-0.720	-0.113	0.022	-0.070	172
Brownsville-Harlingen-San Benito, TX MSA	396,371	7	52	-0.920	-0.954	-0.955	-0.239	-0.280	-0.811	-0.068	-0.001		-0.210	173
Wausau, WI MSA	131,612	3	16	-0.923	-1.013	-0.446	-0.132	-0.040	-0.731	-0.843	-0.059	0.098	-0.143	174
Greenville-Spartanburg-Anderson, SC MSA	1,096,009	5	507	-0.938	-0.923	-0.480	-0.126	-0.174	-1.647	-0.794	-0.252	-0.011	-0.118	175
Scranton--Wilkes-Barre--Hazleton, PA MSA*	614,565	2	27	-0.948	-1.006	-0.503	-0.147	-0.257	-0.495	-0.011	0.018	0.205	-0.127	176
Augusta-Aiken, GA-SC MSA	516,357	5	66	-0.948	-0.971	-0.499	-0.104	-0.102	-1.687	-0.913	-0.167	0.066	-0.108	177
Fayetteville, NC MSA	315,207	5	25	-0.952	-1.000	-0.575	-0.191	-0.259	-1.631	-0.663	-0.229	0.097	-0.169	178
Pensacola, FL MSA	455,102	5	102	-0.954	-0.980	-0.336	-0.173	-0.162	-1.566	1.158	-0.137	-0.075	-0.165	179
Tyler, TX MSA	204,665	7	13	-0.962	-1.057	-0.541	-0.146	-0.862	-0.116	-0.930	-0.204	0.077	-0.036	180
Macon, GA MSA	356,873	5	20	-0.963	-0.989	-0.606	-0.076	-0.097	-1.734	-1.038	-0.172	0.164	-0.083	181
Davenport-Moline-Rock Island, IA-IL MSA*	362,790	4	28	-0.966	-1.018	-0.532	-0.111	0.184	-1.893	-1.201	-0.051	0.179	-0.158	182
Columbia, SC MSA	627,630	5	139	-0.969	-0.983	-0.431	-0.136	-0.141	-1.177	-0.678	-0.235	-0.054	-0.134	183
Lynchburg, VA MSA	232,895	5	13	-0.982	-1.045	-0.405	-0.168	-0.147	-0.984	-0.329	-0.151	-0.027	-0.164	184

TABLE A3: LIST OF METROPOLITAN INDICES RANKED BY LAND PRICE DIFFERENTIAL, 2005-2010

				Adjusted Differentials					*Raw Differentials*			*Productivity*		
Full Name	Population	Census Division	Obs. Land Sales	Land Value	Land Value (No Wts.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Unavail. Index (z-score)	Const. Price Index	Housing	Tradeables	Land Value Rank
Duluth-Superior, MN-WI MSA*	242,041	4	22	-0.985	-1.046	-0.480	-0.149	-0.058	-0.923	0.266	0.074	0.214	-0.159	185
Elkhart-Goshen, IN MSA	200,502	3	14	-0.995	-1.028	-0.622	-0.097	-0.071	-1.531	-1.100	-0.001		-0.108	186
Benton Harbor, MI MSA*	160,472	3	12	-1.003	-1.120	-0.335	-0.142	0.075	-1.155	1.040	-0.001		-0.173	187
Corpus Christi, TX MSA	391,269	7	74	-1.010	-1.047	-0.633	-0.154	-0.155	-1.222	0.443	-0.230	0.137	-0.150	188
Montgomery, AL MSA	354,108	6	33	-1.023	-1.086	-0.526	-0.136	-0.138	-1.759	-0.897	-0.204	0.047	-0.136	189
Lubbock, TX MSA	270,550	7	45	-1.027	-1.039	-0.628	-0.185	-0.207	-1.611	-1.404	-0.209	0.143	-0.172	190
Bryan-College Station, TX MSA	179,992	7	34	-1.029	-1.058	-0.435	-0.178	-0.634	0.314	-1.110	-0.196	-0.042	-0.102	191
Buffalo-Niagara Falls, NY MSA*	1,123,804	2	104	-1.056	-1.054	-0.593	-0.076	-0.067	-1.215	-0.490	0.034	0.281	-0.090	192
Lafayette, LA MSA	415,592	7	15	-1.074	-1.169	-0.571	-0.118	-0.065	-1.803	-1.327	-0.190	0.087	-0.130	193
Grand Rapids-Muskegon-Holland, MI MSA	1,157,672	3	121	-1.114	-1.144	-0.448	-0.113	-0.176	-0.522	-0.970	-0.122	0.005	-0.110	194
Beaumont-Port Arthur, TX MSA*	378,477	7	60	-1.140	-1.167	-0.731	-0.051	-0.259	-1.492	-0.499	-0.176	0.241	-0.039	195
Killeen-Temple, TX MSA	358,316	7	32	-1.153	-1.187	-0.691	-0.180	-0.219	-1.913	-1.262	-0.260	0.135	-0.169	196
Lansing-East Lansing, MI MSA	453,603	3	40	-1.154	-1.164	-0.451	-0.112	-0.083	-0.613	-1.089	-0.011	0.081	-0.124	197
St. Joseph, MO MSA*	106,908	4	12	-1.155	-1.251	-0.619	-0.112	0.000	-2.497	-1.119	-0.050	0.219	-0.029	198
Kalamazoo-Battle Creek, MI MSA*	462,250	3	31	-1.163	-1.175	-0.517	-0.124	-0.110	-0.993	-0.941	-0.062	0.106	-0.131	199
Mobile, AL MSA	591,599	6	135	-1.176	-1.186	-0.463	-0.147	-0.272	-2.767	0.015	-0.155	-0.020	-0.131	200
Flint, MI PMSA*	424,043	3	85	-1.179	-1.152	-0.681	-0.010	-0.037	-0.528	-0.955	-0.010	0.306	-0.034	201
Longview-Marshall, TX MSA	222,489	7	14	-1.202	-1.245	-0.619	-0.123	-0.377	-2.513	-0.903	-0.290	0.028	-0.092	202
Erie, PA MSA*	280,291	2	29	-1.297	-1.354	-0.611	-0.163	-0.211	-0.980	1.080	-0.042	0.185	-0.158	203
Appleton-Oshkosh-Neenah, WI MSA	385,264	3	79	-1.303	-1.294	-0.364	-0.090	-0.058	-0.434	-0.544	-0.068	-0.084	-0.110	204
Toledo, OH MSA*	631,275	3	107	-1.317	-1.322	-0.540	-0.096	-0.217	-2.296	-0.494	-0.010	0.135	-0.093	205
Fort Smith, AR-OK MSA	225,132	7	18	-1.336	-1.409	-0.650	-0.222	-0.200	-1.839	-0.454	-0.205	0.089	-0.217	206
Albany-Schenectady-Troy, NY MSA	906,208	2	120	-1.381	-1.369	-0.173	-0.026	-0.067	-0.241	-0.279	-0.004	-0.242	-0.049	207
Sherman-Denison, TX MSA	120,030	7	19	-1.410	-1.390	-0.728	-0.160	-0.024	-1.719	-1.090	-0.001		-0.112	208
Peoria-Pekin, IL MSA*	357,144	3	25	-1.417	-1.447	-0.513	-0.060	0.003	-0.588	-1.181	0.044	0.130	-0.093	209
Syracuse, NY MSA*	725,610	2	65	-1.452	-1.456	-0.595	-0.091	-0.040	-1.782	-0.549	-0.016	0.158	-0.117	210
Binghamton, NY MSA*	244,694	2	16	-1.494	-1.571	-0.699	-0.104	0.088	-1.494	0.262	-0.035	0.235	-0.151	211
Youngstown-Warren, OH MSA*	554,614	3	49	-1.507	-1.526	-0.739	-0.169	-0.232	-0.842	-0.909	-0.039	0.271	-0.166	212
Evansville-Henderson, IN-KY MSA	305,455	3	33	-1.531	-1.667	-0.632	-0.136	-0.347	-1.385	-1.000	-0.070	0.136	-0.117	213
Sioux City, IA-NE MSA*	123,482	4	17	-1.670	-1.770	-0.822	-0.227	-0.590	-1.938	-1.276	-0.149	0.231	-0.172	214
Glens Falls, NY MSA	128,774	2	21	-1.699	-1.681	-0.291	-0.131	-0.292	-2.636	0.583	-0.069	-0.240	-0.125	215
Saginaw-Bay City-Midland, MI MSA*	390,032	3	41	-1.736	-1.763	-0.629	-0.118	-0.165	-0.236	-0.620	-0.035	0.122	-0.132	216
Utica-Rome, NY MSA*	293,280	2	15	-1.809	-1.889	-0.575	-0.082	-0.267	-1.495	-0.556	-0.048	0.041	-0.084	217
Rochester, NY MSA*	1,093,434	2	110	-1.883	-1.896	-0.538	-0.089	-0.071	-0.614	0.071	0.007	0.038	-0.122	218
Census Divisions:														
New England	8,966,068	1	530	0.050	0.010	0.423	0.092	0.117	0.912	0.240	0.126	-0.332	0.072	5
Middle Atlantic	36,338,768	2	4,567	0.323	0.278	0.262	0.072	0.121	0.144	0.080	0.165	-0.013	0.059	2
East North Central	34,462,007	3	8,534	-0.407	-0.405	-0.272	-0.036	-0.047	-0.689	-0.299	0.030	0.146	-0.038	6
West North Central	12,363,802	4	2,206	-0.495	-0.513	-0.339	-0.063	-0.085	-1.002	-0.900	0.017	0.173	-0.059	7
South Atlantic	41,912,174	5	19,501	0.105	0.109	-0.050	-0.031	-0.032	0.015	0.177	-0.102	0.017	-0.023	4
East South Central	9,366,975	6	1,473	-0.629	-0.642	-0.419	-0.105	-0.138	-0.934	-0.418	-0.141	0.103	-0.096	9
West South Central	26,109,488	7	4,823	-0.567	-0.569	-0.521	-0.066	-0.080	-0.526	-0.795	-0.164	0.198	-0.066	8
Mountain	15,672,803	8	14,517	0.148	0.157	-0.056	-0.040	-0.084	0.296	-0.046	-0.096	0.034	-0.022	3
Pacific	40,847,165	9	10,840	0.677	0.643	0.606	0.080	0.089	0.668	0.988	0.089	-0.306	0.080	1
Metropolitan Population:														
Less than 500,000	31,264,023		1,378	-0.525	-0.563	-0.225	-0.065	-0.077	-0.438	-0.041	-0.055	0.000	-0.063	4
500,000 to 1,500,000	55,777,644		3,253	-0.411	-0.423	-0.202	-0.053	-0.066	-0.345	-0.159	-0.060	0.021	-0.052	3
1,500,000 to 5,000,000	89,173,333		8,168	0.163	0.159	0.074	0.013	0.009	0.131	0.174	0.005	-0.016	0.015	2
5,000,000+	49,824,250		3,997	0.613	0.589	0.316	0.078	0.113	0.173	0.012	0.103	-0.022	0.073	1

Figure A: Shrunken vs. Unshrunken Land Values

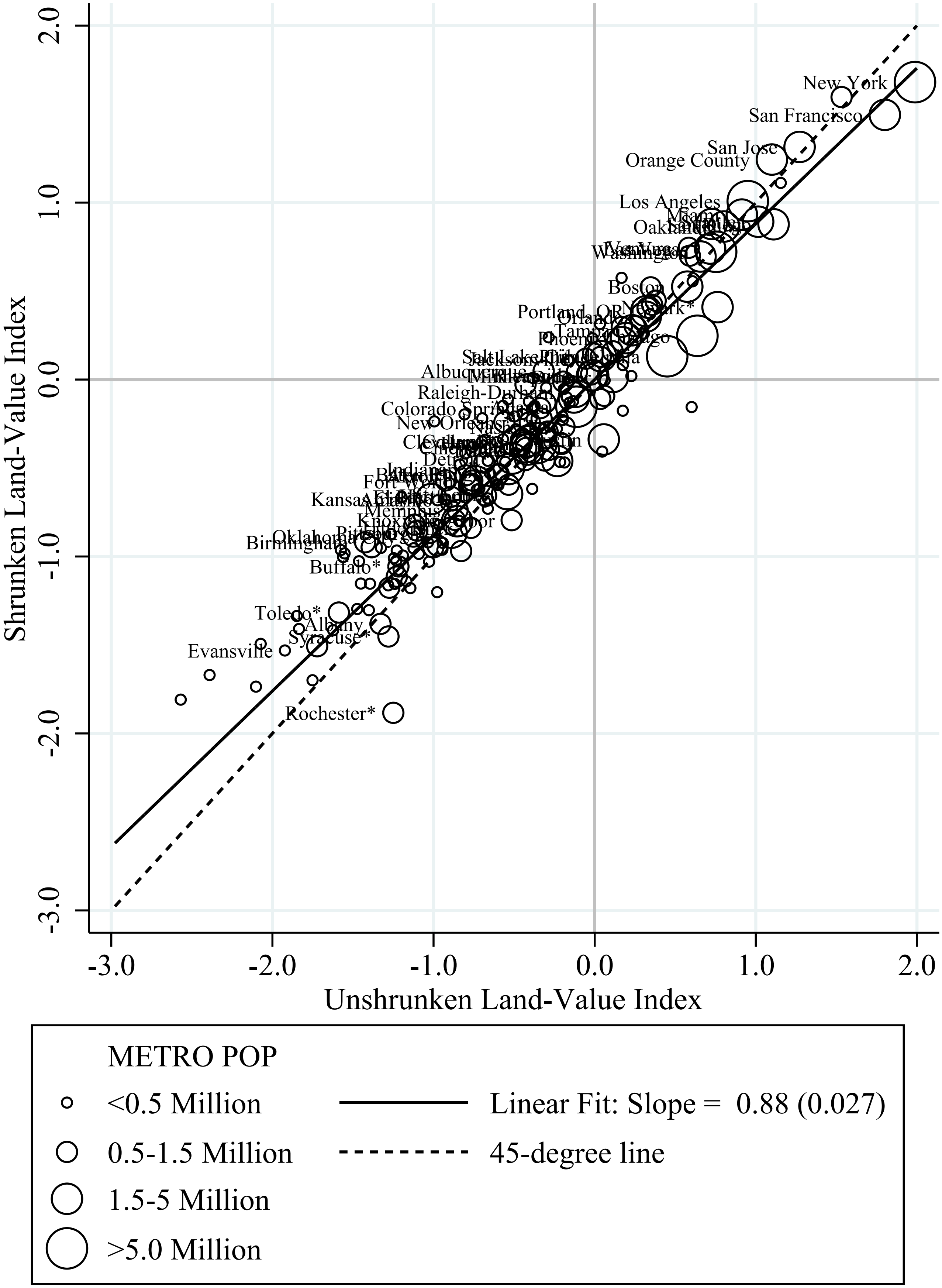

Figure B: Weighted vs. Unweighted Land Values

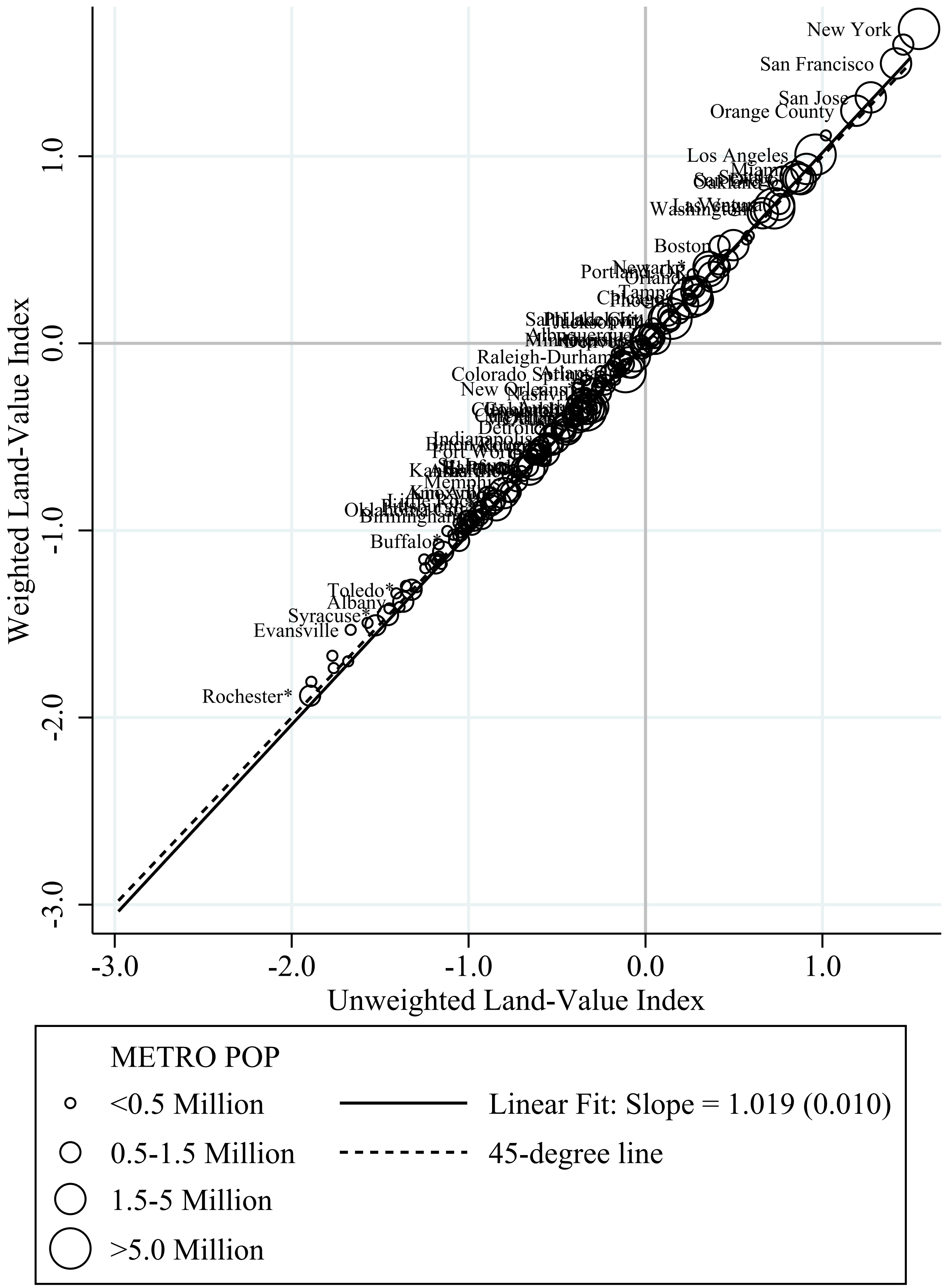

Figure C: Residential vs. Overall Land Values

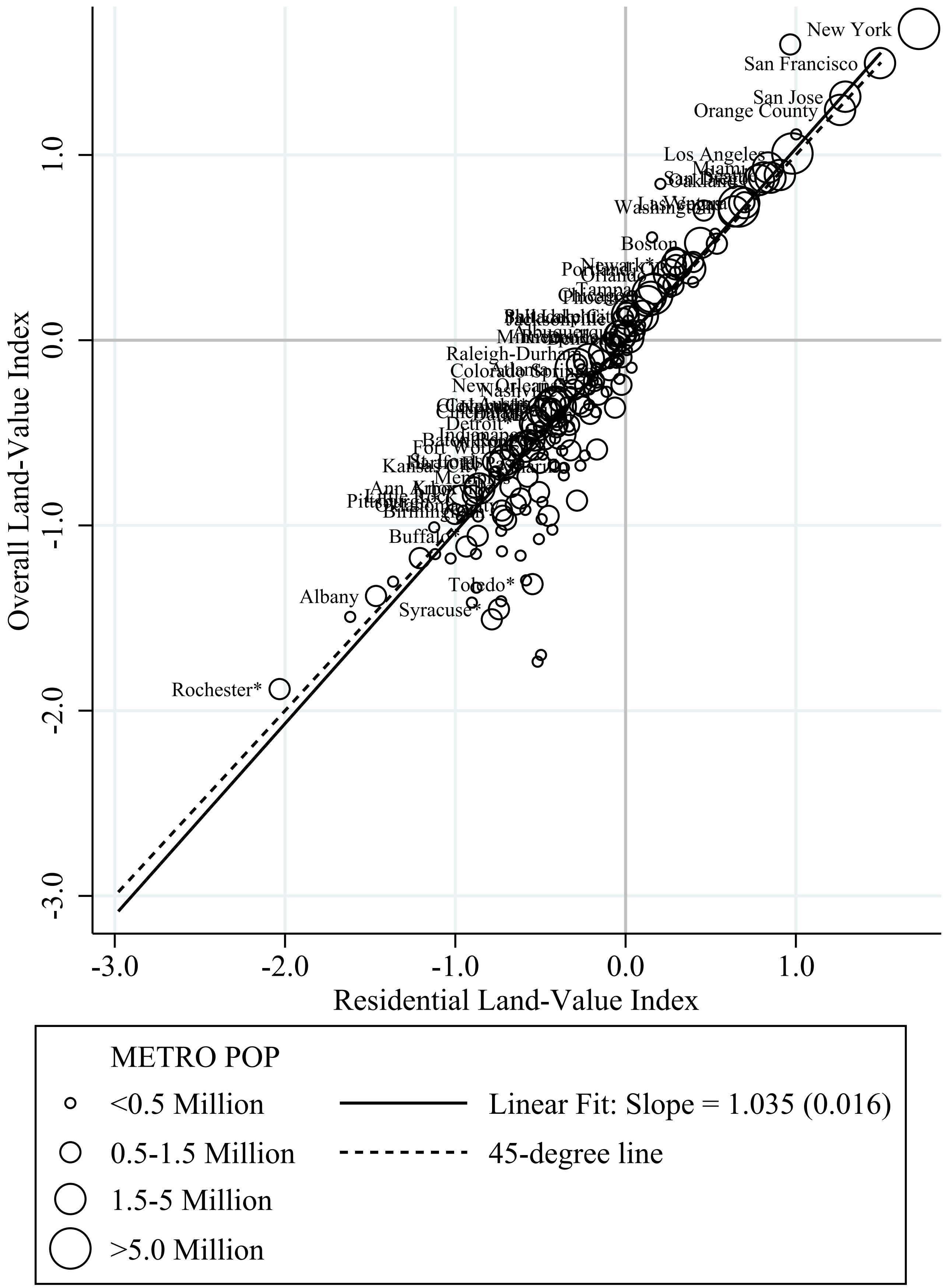

Figure D: Construction Wages vs. Overall Wages

Figure E: Construction Prices vs. Construction Wages