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ABSTRACT

We use metro-level variation in both land and non-land input prices to test and estimate a housing production function and differences in local factor productivity. The econometric model implies that the typical cost share of land is one-third, and substitution with non-land inputs is inelastic. More stringent geographic and regulatory constraints increase housing prices relative to input costs. Disaggregated analysis finds state-level constraints are costliest, and provide a Regulatory Cost Index (RCI) independent of demand factors. Housing productivity falls with city population. The costs of land-use regulations 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). Furthermore, the price of housing varies greatly across urban areas. While demand factors drive much of this price variation, the role of supply factors, in particular regulatory constraints such as zoning, has recently received substantial attention (e.g., Glaeser, et al. 2006, Saiz 2010). Many commentators blame land-use restrictions for declining housing affordability (e.g. Levine 2005), housing-price volatility (e.g. Paciorek 2013), as well as rising wealth inequality (e.g. Summers 2014).[1] Yet these regulations are locally supported and are argued to improve local quality of life and the provision of public goods (Hamilton 1975, Brueckner 1981, Fischel 1985). Straightforward analyses of the effect of land-use restrictions on housing prices cannot distinguish whether price increases are due to increases in demand or reductions in supply. Thus, the social benefits of land-use regulation remain controversial.

In this paper, we estimate an intuitive but previously untested model of the relationship between housing prices, land values, and constraints on housing production that solves this identification problem. It embeds a translog cost function (Christensen et al. 1973) for housing into an equilibrium system of urban areas that simultaneously accounts for how supply and demand factors affect the price of housing separately from the price of land (Roback 1982, Albouy 2016). 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 by examining how these constraints drive a wedge between output (housing) prices and input (land and construction) costs. We find strong evidence that land-use constraints impose a "regulatory tax" that increases the cost of housing.

Furthermore, this methodology allows us to consider the net effect of regulations on social welfare. We find that more desirable areas tend to be highly regulated. After controlling for local amenities, however, the impact of regulations on quality-of-life appears to be small at best, and is dwarfed by increased housing costs. On net, land-use restrictions

[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." In examining wealth inequality, economists since Ricardo (1817) and George (1881) have sought to quantify the share of property values attributable to land, estimated here.

impose large social costs, and may lower the value of local land.

Our approach also offers a unique method for estimating the housing production function. It uses inter-metropolitan variation in both land and non-land costs, as well as regulatory and geographic constraints, to estimate a cost function for housing services based on duality theory. This method passes several strenuous specification tests, identifies both distribution and substitution parameters and provides evidence that a Constant Elasticity of Substitution (CES) functional form approximates housing costs reasonably well (Fuss and McFadden 1978). With only four variables, the model explains 75 percent of housing-price variation across metros. The housing-to-land price gradient implies that land typically accounts for one-third of housing costs. Curvature in the gradient suggests that the cost shares rises from 15 to 50 percent in high-value areas, consistent with an elasticity of substitution between land and other inputs of about 0.5 for the entire housing stock.

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 "housing productivity" measure complements productivity indices for tradeable sectors — seen in Beeson and Eberts (1989), Shapiro (2006), and Albouy (2016) — and indices for local quality of life — as in Roback (1982), Gyourko and Tracy (1991), Albouy (2008) and others. As predicted, regulatory constraints — measured by the Wharton Residential Land-Use Restriction Index (WRLURI) by Gyourko, Saiz, and Summers (2008) — and geographic constraints — the percent of land unavailable for development (Saiz 2010) — reduce housing productivity. Ordinary least squares estimates suggest a standard deviation increase in aggregate measures of these constraints is associated with 8 to 9 percent higher costs; instrumental variable estimates suggest the cost of regulations is even higher. Among disaggregated regulation measures, state political and court involvement approval have the highest efficiency costs in this metro-level analysis.

Our measure of the loss of housing productivity due to the 11 sub-indices provided by the WRLURI provides a novel Regulatory Cost Index (RCI). While the WRLURI provides a widely-used single index of the stringency of land-use regulations through factor analysis, our index is based on the marginal housing cost each regulation imposes. Unlike the WRLURI, which is strictly ordinal, the RCI has a cardinal interpretation based on estimated economic costs. Also unlike the WRLURI, because the RCI is estimated from the wedge between housing and land and construction costs, it measures a cost shifter that is largely immune to the critique that that land-use regulations are correlated with demand factors, made here and by Davidoff (Forthcoming).[2] Furthermore, while households may sort across locations based on accessibility to jobs and quality of life, it is unlikely that they sort on the wedge between housing and land prices. Thus, the RCI provides a practical and robust measure of the effect of land-use regulation on housing supply.

While our estimates of housing production parameters are not unique, our housing productivity estimates are the first of their kind and should be of interest to policy makers. 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 metropolitan 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 and density, suggesting that there are urban diseconomies of scale in housing production, especially as larger cities are heavily regulated.

2 Previous Literature on Housing Production

Our cost function estimates for housing depend on metro-level variation in construction costs, regulatory and geographic constraints, and transaction-based measures of land values. This multi-component approach appears novel in the literature, although Rosen (1978), Polinsky and Ellwood (1979), and Arnott and Lewis (1979) are relevant early predecessors. McDonald (1981) surveys these and other early estimates, and finds most estimates 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, should be largely immune to this problem.

Thorsnes (1997) is unique among our predecessors in using market transactions for land, with a sample in Portland only.[3] Epple et al. (2010) use an alternative estimator based on separately assessed (not transacted) land and structure values for houses in Alleghany County, PA (Pittsburgh), and estimate an elasticity of substitution close to one and a smaller

[2] Davidoff (Forthcoming) found the same phenomenon in his critique concurrently with this paper - although we focus more on quality-of-life amenities. Our approach is immune to his critique of regulation endogeneity from demand, as it allows us to isolate supply factors from demand factors through input prices.

[3] 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."

cost share of land.[4] These studies focus on new construction; ours is on the entire housing stock, is identified and tested with variation in non-land costs, regulation, and geography.[5]

Moreover, we note that there is a tension in the between studies that find housing production has an elasticity of substitution of one — i.e., a Cobb-Douglas form — and studies that find the elasticity of housing supply varies considerably across space, e.g. Green et al. (2005) and Saiz (2010). As shown in section 3.3, the (partial-equilibrium) elasticity of housing supply in a city j is

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

where σ^Y is the elasticity of substitution between land and non-land inputs, and ϕ_j^L is the local cost share of land. With Cobb-Douglas technology, this elasticity is constant, unless the underlying distribution parameter changes considerably across cities. On the other hand, if $\sigma^Y < 1$, then ϕ_j^L rises with the relative price of land, implying that more expensive markets typically have lower elasticities of supply.

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. Davis and Palumbo (2008) use time series methods to estimate that the cost share of land in a sample of large U.S. metropolitan areas rose considerably from 1984 to 2004. Ihlanfeldt (2007) takes assessed land values from tax rolls in 25 Florida counties, and finds that land-use regulations predict higher housing prices but lower land values in a reduced-form framework. Glaeser and Gyourko (2003) and Glaeser et al. (2005) use an enhanced residual method to infer land values, and in a sample of 20 cities — in a model without substitution between land and non-land inputs — find that housing and land values differ most in cities where rezoning requests take the longest.[6] They also find that the price of units in Manhattan

[4] Ahlfeldt and McMillen (2014) obtain similar elasticities 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 proportions that have become suboptimal subsequently to construction 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.

[5] Jackson et al. (1984) consider upwards and downward biases from aging (structure depreciation, site selection, and technological change). They estimate an overall elasticity of substitution of 0.5, and find is slightly *smaller* for newer units.

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

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.

Unlike these studies, our approach (i) produces results that may be applied nationwide, (ii) examines the precise costs of land-use restrictions with a flexible technology, and (iii) offers tests of the validity of our specification.

3 Model of Land Values and Housing Production

Our econometric model uses a cost function for housing embedded within a general-equilibrium model of urban areas, similar to one proposed, but not pursued, by Roback (1982).[7] Albouy (2016) develops predictions on how local productivity should affect housing and land values differently, but lacks the data to test them.[8] The national economy contains many cities indexed by j, which produce a numeraire good, X, traded across cities, and housing, Y, which is not traded across cities, and has a local price, p_j. Cities differ in their productivity in the housing sector, A_j^Y, which we emphasize is distinct from an elasticity of supply.

3.1 Cost Function for Housing with Productivity Shifts

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

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

where F_j^Y is concave and exhibits constant returns to scale (CRS) at the firm level. Housing productivity, A_j^Y, is a city-level characteristic that may be determined endogenously by city characteristics such as population size. 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

[7] 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."

[8] van Nieuwerburgh and Weill (2010) embed a Roback-style model in a dynamic framework, which they use to study the impact of rising wage dispersion as well as land-use restrictions on price dispersion across metropolitan 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 dynamic framework has an inflexible production technology without land, with the national number of new houses fixed by year.

mobile capital. Unit costs in the housing sector, equal to marginal and average costs, are $c^Y(r_j, v_j; A_j^Y) \equiv \min_{L,M}\{r_j L + v_j M : F^Y(L, M; A_j^Y) = 1\}$.[9]

We assume the housing market in city j is perfectly competitive.[10] Then, in cities with positive production (see section 3.5), equilibrium housing prices equal the unit cost:

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

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 in housing.

We adopt a hat notation in which $\hat{z}^j$ 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 (3) expresses how housing prices vary with input prices and productivity: $\hat{p}_j = \phi^L \hat{r}_j + (1 - \phi^L)\hat{v}_j - \hat{A}_j^Y$. 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.[11] 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 (3), drawn in figure 1B, is

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

[9] The use of a single function to model the production of a heterogenous housing stock is well established in the literature, beginning with Muth (1969) 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.

[10] 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. (2005) 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.

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

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 approximately $\phi_j^L = \phi^L + \phi^L(1 - \phi^L)(1 - \sigma^Y)(\hat{r}_j - \hat{v}_j)$, and increases with $\hat{r}_j - \hat{v}_j$ when $\sigma^Y < 1$.

The estimates of $\hat{A}_j^Y$ assume that a single elasticity of substitution describes production in all cities. If this elasticity varies, the estimates will conflate a lower elasticity with lower productivity. Figures 1A and 1B illustrate this possibility by comparing the case of $\sigma^Y = 1$, in solid curves, with $\sigma^Y < 1$, in dashed curves. When production has low substitutability, the cost curve is flatter, as producers are less able to substitute away from land in higher-value cities. Thus low productivity and low substitutability have the same net observable consequence for housing costs, but not for housing production.

Appendix A 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}:

$$- \phi^L(1 - \phi^L)(1 - \sigma^Y)(\hat{r}_j - \hat{v}_j)(\hat{A}_j^{YL} - \hat{A}_j^{YM}). \tag{5}$$

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.

This model also provides the partial-equilibrium elasticity of housing supply from (1)

$$\hat{Y}_j = \sigma^Y \frac{\left(1 - \phi^L\right)^{\sigma^Y} \left(p^j A_Y^j / v^j\right)^{\sigma^Y - 1}}{1 - (1 - \phi^L)^{\sigma^Y} \left(p^j A_Y^j / v^j\right)^{\sigma^Y - 1}} \hat{p}_j = \sigma^Y \frac{1 - \phi_j^L}{\phi_j^L} \hat{p}_j = \eta_j^Y \hat{p}_j \tag{6}$$

as $\phi_j^L = (1 - \phi_L)^{\sigma^Y} \left(p^j A_Y^j / w^j\right)^{\sigma^Y - 1}$. Thus, if $\sigma^Y < 1$, cities that have high relative land values, or productivity biased against land, will have lower elasticities. To allow differing housing supply elasticities with a Cobb-Douglas production function, some underlying mechanism is needed to shift the distribution parameter, ϕ_L, endogenously, or another mechanism, such as land supply, is needed to account for differences in housing supply.[12]

[12] We examined the data for heterogeneity in σ_j^Y, but did not find significant shifters using our methodology. Note that Saiz (2010) assumes $\sigma^Y = 0$, but allows for heterogeneous land supply in a mono-centric city, with differences in the arc of expansion, Λ_j, explaining city-specific elasticities. Taken literally, his model implies $\eta_j^Y = 2/\phi_j^L \geq 2$. The majority of his elasticity estimates are below 2, suggesting the model be amended.

3.2 Adapting and Testing the Translog 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:

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

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 homogeneity 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 observable determinants Z^j and an unobserved component, ζ_j, $\hat{A}_j^Y = -Z^j(\gamma) - \zeta_j$. The vector Z may be partitioned into geographic and regulatory components $Z = [Z^G, Z^R]$. The error term ε_j may come from mis-specification or measurement error.

The homogeneity restrictions imposed in (8) are for a unit-cost function, which assumes constant returns to scale at the firm level. Therefore, we interpret evidence of homogeneity in input prices as indirect evidence for constant returns at the firm level. Returns to scale may still vary with size through A_Y^j, as suggested by the evidence in section 6.2 below.

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 and to test a translog cost function using such a wide cross-section of input and output prices for housing or any other good.

The econometric model allows us to test for the popular Cobb-Douglas (CD) technology. This 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 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 A, $\gamma_2 Z^j/2\beta_3 = \hat{A}_j^{YM} - \hat{A}_j^{YL}$ 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. This implies that if land-use regulations are biased against land, housing costs will rise disproportionately with regulations in cities with higher land values. Furthermore, we can see if the elasticity of substitution varies with Z^j by adding the term $(\hat{r}_j - \hat{v}_j)^2\, Z^j\gamma_3$.[13]

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 simultaneously with housing prices from differences in 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., higher quality of life must offset high prices or low wages, after taxes. Q_j^k is normalized such that $\hat{Q}_j^k$ of 0.01 is equivalent in utility to a one-percent rise in total consumption. s_y^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 $(1 - \tau)\, s_w \hat{w} \equiv \mu^X (1 - \tau^X) s_w^X \hat{w}_j^X + \mu^Y (1 - \tau^Y) s_w^Y \hat{w}_j^Y$. Unobserved heterogeneity in preferences can affect the value of $\hat{Q}_j$ on

[13] 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 $(\hat{A}_{0j}^{YM} - \hat{A}_{0j}^{YL}) = 0$. We do not find interactions for the quadratic interaction to be significant and thus have left a heterogeneous elasticity of substitution out of the remainder of the analysis.

the margin, and will affect housing prices in tandem as a demand shifter, but do not affect supply in A_Y^j.

Traded output has a uniform price across cities and is produced with CRS and CD technology, with A_j^X being factor neutral. We assume land commands the same price in both sectors. 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 all local amenities — affecting quality-of-life, and production in both traded and housing sectors — minus federal tax payments. Therefore, improvements in productivity A_Y may not lead to large reductions in the price of housing p, as land values should rise in response.

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 residual is either unobserved housing productivity, ζ_j, or a general error term ε_j which may represent specification or measurement error, market power in the housing sector, or disequilibrium forces causing prices to deviate from costs.

Identification requires that land values are uncorrelated with unobserved determinants of A_j^Y in the residual, ζ_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 $E[\zeta_j + \varepsilon_j | Z_j, \hat{r}_j, \hat{v}_j] \neq 0$. 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 exhaustive, or can at least capture remaining variation in ζ_j.[14]

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.[15]

An additional concern regarding identification in the econometric model is that regulatory constraints may be endogenously determined and correlated with unobseved supply factors. We follow Saiz (2010) in considering two instruments for regulatory constraints. The first is the proportion of Christians in each metro area in 1971 who were adherents of "nontraditional" denominations (Johnson et al. 1974). The second is the share of local government revenues devoted to protective inspections according to the 1982 Census of Governments (Bureau of the Census 1982). Saiz argues that the nontraditional, and especially Evangelical, Christians measured by the first instrument have an "ethics and philosophy ... deeply rooted in individualism and the advocacy of limited government role" (p. 1276) that is associated with a less stringent regime of land use regulations. Saiz also argues that a higher share of expenditures related to protective inspections is indicative of a general tendency for government to regulate economic activity, which extends to residential land

[14]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.

[15]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.

use. Saiz's model requires that the instruments be uncorrelated with both unobserved demand and supply factors; our cost model is less stringent in requiring that the instruments be uncorrelated with unobserved supply factors alone.

3.5 Durable Housing and Slack Housing Production

The equilibrium condition 3 for housing production requires the replacement cost of a housing unit to equals its market price. Because housing is durable, this condition may not bind in cities where housing demand is so weak that many homes are worth less than their replacement costs (Glaeser and Gyourko 2005). In this case, the systematic slackness between output and input prices in ε will be confused for unobserved productivity ζ_j^Y, and could bias our estimtas. Technically, new housing units are produced in all of the metros, as measured by building permits. However, the equilibrium condition will likely be slack in some neighborhoods of metros that have weak population growth. We indicate weak growth with an asterisk ($*$) in metros 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.

To address this issue econometrically, we estimate specifications that control for building permitting intensity and population growth at the metropolitan level, together with interactions of those terms with indicator variables for whether permitting intensity is below the 25th percentile, and whether population growth was negative from 1970 to 2010. As seen in section 5.2, the estimates do not change meaningfully in these specifications.[16]

3.6 Dynamics and Option Value

In a dynamic model with certainty, Arnott and Lewis (1979) demonstrate that static models like ours produce 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

[16]We also considered specifications that exclude areas in the bottom deciles of population growth or building permits issued as a proportion of the housing stock. The results do not change qualitatively in those specifications, which we omit for space.

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.[17]

4 Data and Metropolitan Indicators

4.1 Housing Price, Land Value, Wage and Construction Prices

Housing-price and wage indices for each metro area, j, and year, t, from 2005 to 2010, are based on 1% samples from the American Community Survey. As described fully in Appendix B, we regress the logarithm of individual housing prices $\ln p_{ijt}$ on a set of controls $\mathbf{X}_{ijt}$, and indicator variables for each year-MSA interaction, ψ_{ijt}, in the equation $\ln p_{ijt} = \mathbf{X}_{ijt} + \psi_{ijt} + e_{ijt}$. The indicator variables ψ_{ijt} provide the metro-level indices, denoted $\hat{p}$.[18] We aggregate the inter-metropolitan index of housing prices, $\hat{p}_{jt}$, normalized to have mean zero, across years for display.

The land-value index is taken from Albouy, Ehrlich, and Shun (2016), who describe it in far greater detail. It is based on a similar regression framework, with controls for acreage and intended use, applies shrinkage techniques from Kane and Staiger (2008) to correct for measurement error due to sampling variation. We use a version weighted to represent where residential housing units are located.

Our main price index for construction inputs comes from the Building Construction Cost data from the RS Means company. This index covers several types of structures and is common in the literature, e.g., Davis and Palumbo (2008), and Glaeser et al. (2005). Appendix B discusses the construction price index in detail.

Metropolitan wage differentials are calculated 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, $\hat{w}^Y_j$. As seen in appendix figure A, $\hat{w}^Y_j$

[17] Regulations may also "follow the market" (Wallace 1988), potentially limiting their effects on land and housing prices. Our framework of comparing house prices to input costs offers a substantially different test of whether regulations follow the market and considers a broader range of regulations across the United States. Capozza and Li (1994) show that high option values may lead to delayed investment, and a housing stock of lower value. For instance, a developer may forego demolishing a two-story house to rebuild a new one, in case he may want to build a condo tower. Regulations can remove that uncertainty, but still lower the value of the land beneath it.

[18] Alternative methods of estimating housing-price differences, such as letting the coefficient β vary across cities, produces similar indicators.

is similar to, but more dispersed than, overall wages, $\hat{w}_j$.[19]

The housing-price, land-value, construction cost, and construction-wage indices are reported in the columns 2 through 5 of table 1. They tend to be positively correlated with each other and metro population, reported in column 1, highlighting the importance of having both measures of land and non-land input costs.

4.2 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.[20] The base data for the WRLURI is for the municipal level; we calculate the WRLURI and subindices at the MSA level by weighting the individual municipal values using sampling weights provided by the authors, multiplied by each municipality's population proportion within its MSA. The authors construct a single aggregate WRLURI index through factor analysis: we consider both their aggregate index and the subindices in our analysis. We renormalize all of these as $z-$scores, with a mean of zero and standard deviation one, weighted by the number of housing units. 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 A2 shows that the highest WRLURI index in our sample is in Boulder, CO, and the lowest is in Mobile, AL; the most geographically constrained is in Santa Barbara, CA, and the least is in Lubbock, TX.

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

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

5 Cost-Function Estimates

The indices from section 4 provide considerable variation to test and estimate the cost function presented in section 3, and to examine how costs are influenced by geography and regulation 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 gradient in the quadratic regression implies that the average cost-share of land increases with land values, yielding an imprecise estimate of the elasticity of substitution of 0.2.[21] 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 simple cost parameter estimates are biased, as land values are positively correlated with construction prices and geographic and regulatory constraints.

Construction prices are plotted against land values in figure 2A. These data help to estimate the cost surface shown in figure 2B, without controls. As before, cities with housing prices above this surface are inferred to have lower housing productivity. Figure 2A plots the level curves for the surface in 2B, 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.

Moving from these illustrations to our core model, table 2 presents cost-function es-

[21] 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 $\beta_3 \leq 0.5\beta_1(1-\beta_1)$.

timates with the aggregate geographic and regulatory indices. Columns 1 and 2 impose CD production, as in equation 9; column 2 imposes the restriction of CRS in equation 8, which is rejected at the 5% significance level. The Cobb-Douglas restriction in equation 9 is also rejected at the 5% significance level. The CRS restriction is not rejected in the more flexible translog equation, presented in columns 3 and 4.

The results in column 5 examine whether the constraints are factor-biased. 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 6 uses wage levels in the construction industry instead of the construction prices. The results in column 6 are similar to those in column 4. However, the CRS restriction fails at standard significance levels. While these results cross-validate our results using construction prices, they also suggest that the construction-price index is a more appropriate input cost measure than the construction-wage index.

Overall, the estimates in table 2 produce stable values of 0.34-0.38 for the cost-share of land parameter, ϕ_L. The restricted regression in columns 4 to 6 estimate an elasticity of substitution σ^Y of around 0.4. Furthermore, we find that one standard deviation increases in the geographic and regulatory indices predict 9- and 8-percent increases in housing costs, respectively. These mutually reinforcing estimates support the key prediction that both geographic and regulatory constraints reduce efficiency in the production of housing services.

5.2 Estimate Stability

Several exercises, reported in table 3, help gauge the stability and robustness of our estimates. Our base specification from column 4 of table 2 is reproduced in column 1 for convenience. First, in column 2 we use a parametereized specification using values from Albouy (2009), based on his literature survey: he sets a cost share of land of $\phi_L = 0.23$, lower than in column 1, and an elasticity of substitution of $\sigma_Y = 0.67$, that is higher. This specification predicts stronger effects of constraints: the geographic coefficient is now 0.14, while the regulatory coefficient is 0.10. In general, the key prediction that regulatory constraints lower efficiency persists for a wide range of production parameters.

Second, we use three alternative land-value indices: i) for residential land uses only; ii) "raw" measures, unadjusted for characteristics; and iii) unshrunken land-value indices.

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

Land is defined as residential if its proposed use is listed as single-family, multi-family, or apartments. These plots should be located in areas more similar to existing housing and are intended for immediate construction, not to be held for later use. Raw 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 re-weighted by location. The unshrunken indices are derived directly from the regression technique described in Albouy, Ehrlich, and Shun (2016), without applying the Kane and Staiger (2008) shrinkage technique. The results for the residential land values in column 3 are nearly identical to those in column 1. In columns 4 and 5, the estimated land share is lower as we see more dispersion in the land index, which causes attenuation: the first, from omitted variables and mismatched locations; the second, from sampling error. Nevertheless, the results involving the regulatory and geographic constraints become even stronger.

Third, we split the sample into two periods: a "housing-boom" period, from 2005 to 2007, and a "housing-bust" period, from 2008 to 2010. The results, seen in columns 6 and 7, are not statistically different from those in the pooled sample. However, the former period does have stronger effects of geographic and regulatory constraints. These results support the model as the constraints should be more binding on the margin when the housing market is tighter. The later sample implies a lower elasticity of substitution. This may come from a perceived drop in the option value of undeveloped land in the highest-value areas, combined with measurement error in the housing price index resulting from ACS respondents' imperfect awareness of current market conditions (Ehrlich .

Columns 8 and 9 use the full sample and base land value index, but add controls for building activity and population growth to address concerns from section 3.5 that the builders' zero profit condition may be slack in low-growth areas. Column 8 controls for the ratio of annual building permits issued to units in the housing stock and the logarithm of population growth from 1970 to 2010. The coefficient on the proportion of building permits issued implies that a one percent increase in permitting is associated with 3.9% lower housing costs, which we interpret as implying that building activity is more intense in areas with higher productivity in the housing sector. The coefficient on population growth is not statistically significant. Column 9 adds interaction terms for permitting activity times an indicator if permitting is below the 25th percentile in the sample, and for population growth times an indicator for negative population growth. The first interaction is statistically insignificant, while the positive coefficient on the second interaction suggests that slackness in the housing market expands the more a metro's population shrinks — providing strong support for Glaeser and Gyourko's (2005) model of kinked housing supply. Nonetheless, the main results do not change appreciably from the baseline specification in column 1, when we control for these interactions.[23]

5.3 Disaggregate Indices and the Regulatory Cost Index

As discussed previously, 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 2, 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 may still carry some information. The almost significant negative coefficient on exactions (sometimes known as "impact fees") is particularly suggestive, as these are thought to be a relatively efficient land-use regulation, especially when they help pay for infrastructure improvement (Yinger 1998).[24]

The regression coefficients are positively related to, albeit not identical to, the factor loadings. Moreover, they are based on what appears to be the relative economic importance of each of the subindices. The predicted value $Z_j^R \hat{\gamma_1^r}$ then provides a cardinal estimate of

[23]We have also estimated specifications in which we drop the bottom deciles of observations with the lowest building permits issuance or the lowest population growth rates. The results are qualitatively similar.

[24]Our result that state regulations are the most important in driving housing inefficiency is consistent with results in Gleaser and Ward (2009) that more local regulations may have more limited effects.

the costs of regulations, which we call the "Regulatory Cost Index" or RCI, and analyze below.

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

The tight fit of the cost-function specification, as measured by the coefficient of variation (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 3 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 the approximate formula for cost share in section 3.1, the typical cost share of land ranges from 16 percent in Rochester to 49 percent in New York City. The associated partial elasticities of housing supply η_j^Y, range from 3.0 to 0.6.[25]

5.4 Instrumental Variables Estimates

To assess the potential concerns regarding the endogeneity of land values and land-use regulations discussed in section 3.4, Table 5 presents instrumental variables estimates of the base Cobb-Douglas and translog specifications in table 2.[26] Columns 1 and 2 present instrumental variables versions of the Cobb-Douglas estimates in column 2 of table 2. Column 1 uses inverse distance from the sea and the USDA amenity score as instruments for the differential $(\hat{r} - \hat{v})$. Column 2 adds the nontraditional Christian share and protective inspections share suggested by Saiz as instruments, and treats both the land-value differential and the regulatory index as endogenous. The estimated land share in column 1 is higher than in the OLS estimates at 0.48, although a formal Hausman-style test does not reject the null hypothesis of exogenous land values at the 5% significance level. In column 2, which instruments for both the land-value differential and the regulatory index, the estimated land share is approximately one-third, similar to the OLS results. Instrumented

[25] Our housing supply elasticities are positively related with those provided by Saiz (2010): a 1-point increase of our elasticity predicts a 1.38-point (s.e. = 0.28) in his. The Regulatory Cost Index is positively correlated with the Wharton Residential Land Use Regulatory Index z-score measure, with a correlation coefficient of 0.74.

[26] Table A1 presents first-stage estimates including assessments of instrument strength and validity.

increases in regulatory stringency result in substantially higher and less precise estimates for their efficiency costs.

Translog IV estimates in columns 3 and 4 correspond to OLS estimates in column 4 of table 2. Column 3 uses the levels and squares of the USDA amenities score and inverse distance to the sea, as well as their interaction, as instruments for the differentials $(\hat{r}-\hat{v})$ and $(\hat{r}-\hat{v})^2$. Column 4 also uses the nontraditional Christian share and protective inspections share, and their interactions with the first two instruments, as excluded instruments, and treats the regulatory index as an endogenous variable. The estimated cost shares of land are again somewhat higher than in the OLS estimates, but are also less precise. The IV estimates efficiency cost of regulations in column 4 are 13 log points per standard deviation, larger than the OLS but smaller than the IV Cobb-Douglas case. The estimated elasticities of substitution in columns 3 and 4 are very imprecise, but rather close to one-half.

The IV estimates are largely consistent with our OLS estimates. They suggest a somewhat higher cost share of land and larger impacts of regulatory constraints, while being less precise. The two bottom rows of table 5 report Wooldridge's (1995) test of regressor endogeneity and Sargan's (1958) over-identification test of instrument exogeneity. The results of these tests are mixed: the results in columns 2 and 4 reject the exogeneity of the instrumented regressors, suggesting that the regulatory index may be endogenous. However, columns 3 and 4 reject the over-identifying restrictions.[27] However, as we emphasized earlier, by being based on the wedge between input and output prices, the estimates are not invalidated by unobserved differences in demand, only supply. This makes the IV strategy less critical for the asymptotic consistency of our results.

6 Housing Productivity across Metropolitan Areas

6.1 Productivity in Housing and Tradeables

In column 1 of table 6 we list an inferred measures of housing productivity from our favored specification, using both observed and unobserved components of housing productivity, i.e., $\hat{A}_j^Y = Z_j(-\hat{\gamma}) - \hat{\zeta}_j$ assuming $\varepsilon_j = 0$.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,

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

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.[28]

Column 2 reports the RCI, based only on the value of productivity loss predicted by the regulatory subindices, Z_j^R, i.e., $RCI_j = \hat{\gamma}_1^R Z_j^R$. The cities with the highest regulatory costs are in New England, notably Brockton, MA; Manchester, NH; and Lawrence, MA-NH; with Boston topping the list of large cities. The West South Central regions has cities with the lowest RCI: New Orleans, LA; Little Rock, AR; and Baton Rouge, LA. The differences are also quite suggestive. For example, the regulatory environment in Chicago cause it to be 34 percent more efficient at producing housing than Boston.

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 (2016). Figure 3 plots housing productivity relative to trade-productivity. The figure draws a level curve 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 $\hat{A_Y^j} = 0$.[29]

Our estimates of trade-productivity, based primarily on the weighted sum of overall wage levels and land costs are arguably a small improvement over existing estimates. The previous literature — including Beeson and Eberts (1989), Rauch (1993), Gabriel and Rosenthal (2004), Shapiro (2006), and Albouy (2016) — has tried to infer firms' land costs from residential housing costs. As our theory makes clear, truly accurate inferences of land values from housing (and construction costs) require knowledge of A_Y^j. The bias in trade-productivity without land measures is given by $\theta_L/\phi_L \hat{A}_Y$, given by a line in figure 3. This line has a modest slope, suggesting the biases are fairly moderate: cities with the lowest housing productivity, like San Francisco, have their trade-productivity overstated

[28] See Table A2 for the values of the major indices and measures for all of the MSAs in our sample.

[29] 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.

by about 3 percentage points; high-housing productivity cities like Houston and Las Vegas have their trade-productivity understated by 2 percentage points.[30]

Interestingly, trade productivity and housing productivity are negatively correlated. A 1-point increase in trade-productivity predicts a 1.6-point decrease in housing productivity. For instance, coastal cities in California have among the highest levels of trade productivity and the lowest levels of housing productivity. On the other hand, cities like Dallas and Atlanta are relatively more productive in housing than in tradeables. New York, Chicago, Philadelphia, and Las Vegas manage to achieve above average productivity in both sectors. Tucson has the dubious distinction of being the least productive overall when both measures are combined.

6.2 Productivity-Population Gradients with Diseconomies in Housing

Part of the negative relationship between trade and housing productivity estimates appears to relate to city size. This suggests that city-level scale economies may differ considerably in the two sectors. While trade-productivity is known to increase with city size (e.g., Rosenthal and Strange, 2004), economies of scale in housing may be decreasing. This may arise from negative externalities in production from congestion. Since housing is almost always produced on site, tight spaces around construction sites in crowded environments force builders to use more expensive space-saving technologies. Spare land may actually be a useful input to the construction of housing, as well as the flow services it provides.

Furthermore, new construction may impose temporary negative externalities in consumption on incumbent residents. Noise and dust are greater nuisances in denser environments. Moreover, local residents often protest new developments over fears of permanent negative externalities due to increased traffic and blocked views. These fears of negative externalities can cause incumbent residents in populous areas to regulate new development, as discussed below, raising housing costs without directly intending it.

Table 7 examines the relationship of productivity with population levels, aggregated at the consolidated metropolitan (CMSA) level, in panel A, or population density, in panel B. In column 1, the positive elasticities of trade productivity with respect to population of 6 percent are consistent with many in the literature (Ciccone and Hall 1996, Melo et al. 2009).

[30]This line is based on inferring land costs based on the structure of housing, noted in Albouy (2016) building on Muth (1969). Previous studies generally conflated land and housing, implicitly setting $\phi^L = 1$.

When weighted by their expenditure share (0.64) — in column 4 — these elasticities are 3.6 to 4.1 percent. The results in column 2 reveal negative elasticities of housing productivity with respect to population of almost 7 percent; weighted by the expenditure share (0.18) in column 5 it is 1.2 percent. Although this number may not be causal, it is hard to imagine why workers would sort to less productive metros.

Using the RCI — excluding biases introduced by correlated geography and specification errors in ε_j — column 3 presents an arguably more reasonable, but still substantial elasticity: a 10-percent increase in population engenders regulations that raise housing costs by roughly 0.25 percent. Weighted by the housing expenditure share, regulations lower the income-population and density gradients by 0.4 and 0.5 percentage points. These numbers are substantial when the full range of population density is considered, seen in Figure 4. Overall productivity, examined in column 6, increases with population and density at elasticities of only 2.4 and 2.9 percent, much less than trade productivity alone. If we take home-productivity more narrowly, to be only the component predicted by the RCI in column 7, this relationship becomes stronger: the elasticities rise to 3.2 and 3.6 percent.

In the next section, we explore whether fixing the regulatory environment across city sizes could have negative consequences for urban quality of life.

6.3 Housing Productivity and Quality of Life

The model in section 3 predicts that if regulations only reduce housing productivity, then they reduce land values, and increase housing prices — albeit by less than the efficiency cost — 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, regulation raises house prices by increasing demand, rather than by limiting supply. Moreover, so-called "fiscal zoning" may be used to preserve the local property tax base and deliver public goods more efficiently, in support of the Tiebout (1956) hypothesis (Hamilton 1975; Brueckner 1981).

On the other hand, Hilber and Robert-Nicoud (2013) argue that rent-seeking incentives will cause nicer areas to become more highly regulated, inducing a spurious correlation. Levine (2005) argues that incumbent residents fail to change zoning laws as cities grow, causing inefficiently low density and excess commuting, thereby reducing quality of life. To our knowledge, there are only a few estimates of the benefits of land-use regulations, e.g. Cheshire and Sheppard (2002) and Glaeser et al. (2005), both of which suggest low benefits.

To examine this hypothesis we relate our quality-of-life and housing-productivity estimates, shown in figure 5 and Panel A of Table 8. 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 (also shown in column 1). Column 4 implies that a one-point increase in regulatory costs is associated with a 0.2-point increase in quality of life. These estimates ignore how higher quality of life areas may be more prone to regulate.

Controlling for possible confounding factors changes this perspective dramatically, as observable amenities are highly correlated with housing productivity and the RCI. Columns 2 and 5 include controls for natural amenities, such as climate, adjacency to the coast, and the geographic constraint index; columns 3 and 6 add controls for artificial amenities, such as the population level, density, education, crime rates, and number of eating and drinking establishments. In all cases, these controls undo the relationship, reversing the point estimate in sign, so that the RCI estimates suggest regulations could even lower quality of life, albeit insignificantly. Whatever the case, they provide clear evidence that regulations and natural and artificial amenities are positively correlated.

6.4 Net Effects on Welfare and Land Values

The expenditure share of housing is 0.18, so the social cost of land use restrictions, expressed as a fraction of total consumption, is equal to 0.18 times the RCI. For quality-of-life benefits to exceed this cost, the elasticity of quality of life with respect to the RCI must exceed this share.

If we accept the simple regression relationship in column 4 as causal, it would appear that the costs and benefits of regulation balance out exactly. As we see in columns 5 and 6, controlling for amenities renders the relationship between quality of life and regulatory costs economically small and statistically insignificant. Therefore, quality of life benefits cannot outweigh the efficiency costs regulations impose on housing production. The estimates in columns 5 and 6 imply an elasticity of social welfare with respect to housing productivity of roughly 0.2, meaning that regulations which lower housing productivity also reduce social welfare. It is worth noting that most explanations of the endogeneity of land use regulation in these simple regressions imply that that regulation is likely to have even fewer quality of life benefits, and a higher social cost, than we estimate here.

Welfare-reducing regulations may persist 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. The near zero quality-of-life results suggest that outside buyers may not even value the amenities these regulations are meant to preserve. Importantly, our results are at the metropolitan level, and could reflect a Coasean failure, as suggested by Levine (2005). New residents or developers may lack the coordination to buy out the incumbents in particular neighborhoods. As a result, the entire metropolitan area is organized inefficiently, and overall quality-of-life for the city may even fall.

We conclude by considering the overall effect of productivity and regulations on local land values, with estimates in Panel B. The net welfare loss from regulations implies that land should lose value, despite increases in house prices. The simple regressions in columns 1 and 4 reveal that land values are negatively related to housing productivity and even more strongly positively related to the RCI, contrary to our model's predictions. Adding controls for natural and artificial amenities yields estimates with signs consistent with the theory, although they are not statistically distinguishable from zero. Given the limited nature of these results, further research on this subject is certainly warranted. One promising avenue is preference heterogeneity, which we abstract from in our model. While such heterogeneity was of little consequence to our analysis thus far, it does allow for the ultimate incidence of regulatory inefficiency to fall partly on households. Households that have strong tastes for, say, dense cities or the Pacific Coast, are more exposed to inefficient housing production, and may thus be made worse off.[31] As a result, local land owners will suffer less than the full loss of value engendered.

7 Conclusion

The cost function estimates embedded within a general-equilibrium system of cities offers a novel and useful way of isolating supply and demand factors in the determination of housing prices, particularly for land-use regulations. The approach also allows for greater geographic coverage and a broader set of regulations than have previously been considered. The estimated cost function fits the data well and produces estimates with credible economic magnitudes from numerous disparate data sources. The two input prices and two constraint measures together explain 75 percent of the variation in home prices. Further-

[31] Gyourko, Mayer, and Sinai (2013) present a taste-based model, with similar welfare consequences.

more, the numerous specification checks and instrumental variable strategies suggest that the ordinary least squares estimates are likely to be consistent measures of the model parameters. We even find evidence that housing prices are below replacement costs in markets losing population, supporting Glaeser and Gyourko (2005).

Based on the observed housing price gradients, we estimate the average cost share of land in housing is one-third and the elasticity of substitution between land and non-land inputs is, less precisely, one-half. These imply the typical cost share of land ranges from 15 to 50 percent across metros, e.g., 26 percent in Pittsburgh (although that market may be slack), 39 percent in Portland, and 48 percent in San Francisco. These varying cost shares are consistent with housing supply varying in price elasticity across cities.

Moreover, the estimates provide strong support for the hypothesis that geographic and regulatory constraints create a wedge between the prices of housing and its inputs. The disaggregated estimates suggest that state political and court involvement are associated with large increases in housing costs. This is consistent with the difficulty of avoiding broad regulatory effects. We provide a Regulatory Cost Index that quantifies a precise cost of housing regulations, purging the effect of demand factors. We hope this index will be of use to other researchers.

Importantly, cities that are productive in traded sectors tend to be less productive in housing, as the two appear to be subject to opposite economies of scale. Larger cities have lower housing productivity, much of which seems attributable to greater regulation. While some regulations may be welfare enhancing, overall these regulatory costs — as measured by our index — do not appear to improve quality of life for residents once observable amenities are controlled for. Thus, land-use regulations appear to raise housing costs more by restricting supply than by increasing demand. On net, the typical land-use regulation may actually lower land values, and reduces well-being by making housing production less efficient, and housing less affordable.

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

Name of Area	Population (1)	Housing Price (2)	Land Value (3)	Const. Price Index (4)	Wages (Const. Only) (5)	Regulation Index (z-score) (6)	Geo Unavail. Index (z-score) (7)
Metropolitan Areas:							
San Francisco, CA PMSA	1,785,097	0.21	1.42	-0.55	1.68	2.17	0.23
San Jose, CA PMSA	1,784,642	0.21	1.27	-0.46	-0.11	1.71	0.18
Orange County, CA PMSA	3,026,786	0.09	1.19	-0.39	0.03	1.15	0.10
Los Angeles-Long Beach, CA PMSA	9,848,011	0.09	0.96	-0.42	0.84	1.15	0.10
New York, NY PMSA	9,747,281	0.15	1.55	0.03	-0.22	0.56	0.31
Boston, MA-NH PMSA	3,552,421	0.09	0.50	-0.33	1.26	0.24	0.18
Washington, DC-MD-VA-WV PMSA	5,650,154	0.13	0.73	-0.12	0.85	-0.74	0.01
Riverside-San Bernardino, CA PMSA	4,143,113	0.09	0.05	-0.19	0.60	0.44	0.07
Chicago, IL PMSA	8,710,824	0.05	0.26	0.03	-0.60	0.54	0.17
Philadelphia, PA-NJ PMSA	5,332,822	0.06	0.15	0.11	0.64	-0.93	0.16
Phoenix-Mesa, AZ MSA	4,364,094	-0.01	0.30	0.03	0.96	-0.74	-0.10
Atlanta, GA MSA	5,315,841	-0.01	-0.11	0.18	0.03	-1.23	-0.10
Detroit, MI PMSA*	4,373,040	-0.01	-0.44	0.21	-0.31	-0.22	0.05
Dallas, TX PMSA	4,399,895	-0.01	-0.38	0.21	-0.73	-0.98	-0.14
Houston, TX PMSA	5,219,317	0.01	-0.34	0.31	-0.12	-1.01	-0.12
Rochester, NY MSA*	1,093,434	-0.09	-1.90	0.04	-0.61	0.07	0.01
Utica-Rome, NY MSA*	293,280	-0.08	-1.89	0.04	-1.50	-0.56	-0.05
Saginaw-Bay City-Midland, MI MSA*	390,032	-0.12	-1.76	0.12	-0.24	-0.62	-0.03
Metropolitan Population:							
Less than 500,000	31,264,023	-0.23	-0.52	-0.44	-0.08	-0.04	-0.05
500,000 to 1,500,000	55,777,644	-0.20	-0.41	-0.34	-0.07	-0.16	-0.06
1,500,000 to 5,000,000	89,173,333	0.07	0.16	0.13	0.01	0.17	0.01
5,000,000+	49,824,250	0.32	0.61	0.17	0.11	0.01	0.10
Standard Deviations (pop. wtd.)		0.51	0.76	0.14	0.16	0.96	1.01
Correlation with land values (pop. wtd.)		0.89	1.00	0.60	0.66	0.46	0.57

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

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

Specification	Basic Cobb-Douglas (1)	Restricted Cobb-Douglas (2)	Translog (3)	Restricted Translog (4)	Non-neutral Productivity Translog (5)	Restricted Translog w/ Constr Wages (6)
Land-Value Differential	0.360	0.375	0.342	0.376	0.385	0.361
	(0.037)	(0.034)	(0.041)	(0.036)	(0.031)	(0.032)
Construction-Price Differential	1.049	0.625	0.996	0.624	0.615	0.639
	(0.159)	(0.034)	(0.160)	(0.036)	(0.031)	(0.032)
Land-Value Differential Squared			0.033	0.076	0.067	0.072
			(0.033)	(0.034)	(0.029)	(0.031)
Construction-Price Differential Squared			-1.158	0.076	0.067	0.072
			(1.040)	(0.034)	(0.029)	(0.031)
Land-Value Differential X Construction-Price Differential			0.400	-0.152	-0.134	-0.144
			(0.321)	(0.068)	(0.058)	(0.062)
Geographic Constraint Index: z-score	0.092	0.104	0.092	0.093	0.091	0.111
	(0.025)	(0.027)	(0.023)	(0.027)	(0.022)	(0.026)
Regulatory Index: z-score	0.058	0.068	0.072	0.075	0.081	0.063
	(0.013)	(0.013)	(0.013)	(0.014)	(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	856	888
Number of MSAs	207	207	207	207	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	0.060	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	0.431	0.380
				(0.278)	(0.242)	(0.257)

Dependent variable in all regressions is the housing price index. Robust standard errors, clustered by CMSA, reported in parentheses. Data sources are described in Table 1. Restricted model specifications require that the production function exhibits 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.

TABLE 3: SENSITIVITY ANALYSIS TO ALTERNATE LAND MEASURES, SPLIT SAMPLE, AND CONTROLS FOR PERMITS AND POPULATION GROWTH

Specification Dependent Variable	Base Specification Hous. Price (1)	Calibrated Specification (2)	Residential Land Sample Hous. Price (3)	Raw Land Values Hous. Price (4)	Unshrunken Land Values Hous. Price (5)	2005-2007 Boom Sample Hous. Price (6)	2008-2010 Bust Sample Hous. Price (7)	Permits and Population Controls (8)	Permits and Population Non-linear (9)
Land-Value Differential	0.376	0.233	0.384	0.245	0.286	0.366	0.383	0.384	0.367
	(0.036)		(0.039)	(0.028)	(0.033)	(0.040)	(0.037)	(0.032)	(0.033)
Land-Value Differential Minus Construction Price Differential Squared	0.076	0.030	0.068	-0.006	0.060	0.054	0.099	0.064	0.073
	(0.034)		(0.036)	(0.018)	(0.019)	(0.038)	(0.036)	(0.037)	(0.037)
Geographic Constraint Index: z-score	0.093	0.142	0.086	0.105	0.121	0.120	0.069	0.085	0.090
	(.027)	(.031)	(.028)	(.029)	(.031)	(.032)	(.024)	(.026)	(.026)
Regulatory Index: z-score	0.075	0.099	0.076	0.095	0.088	0.092	0.064	0.075	0.075
	(.014)	(.013)	(.016)	(.013)	(.014)	(.016)	(.015)	(.013)	(.012)
Ratio of Building Permits to Housing Units in Current Year								-3.917	-3.766
								(1.145)	(1.189)
Logarithm of Population Growth from 1970 to 2010								-0.016	-0.052
								(0.062)	(0.060)
Ratio of Building Permits Times Permits Below 25th Percentile									0.072
									(6.582)
Log Population Growth Times Population Growth Negative									2.550
									(0.487)
Adjusted R-squared	0.745		0.743	0.727	0.734	0.734	0.764	0.776	0.787
Elasticity of Subsitution	0.349	0.667	0.429	1.062	0.417	0.537	0.159	0.460	0.374
	(0.278)		(0.295)	(0.192)	(0.314)	(0.288)	(0.161)	(0.300)	(0.306)

Robust standard errors, clustered by CMSA, reported in parentheses. Regressions correspond to the restricted specification in column 4 of Table 2. Calibrated specification in column 2 imposes land share of of 23.3 percent and elasticity of substitution of two-thirds, consistent with the calibration in Albouy (2009).

TABLE 4: DISAGGREGATED GEOGRAPHIC AND REGULATORY INDICES AND HOUSING COSTS

Specification	Regulatory Index Factor Loading	Regulatory Index on Subindices	Georaphic Index on Subindices	Restricted Translog
Dependent Variable		Reg Index	Geog 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
			(0.035)	(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 1; constituent components of Wharton Residential Land Use Regulatory Index (WRLURI) are from Gyourko et al (2008). Constituent components of geographical index are from Saiz (2010).

TABLE 5: DEPENDENCE OF METROPOLITAN HOUSING PRICES ON LAND VALUES, CONSTRUCTION PRICES, AND AGGREGATE GEOGRAPHIC AND REGULATORY CONSTRAINTS: INSTRUMENTAL VARIABLES ESTIMATES

Specification	Restricted Cobb-Douglas (1)	Restricted Cobb-Douglas (2)	Restricted Translog (3)	Restricted Translog (4)
Land-Value Differential	0.484	0.333	0.462	0.427
	(0.082)	(0.069)	(0.073)	(0.078)
Land-Value Differential Squared			0.052	0.067
			(0.103)	(0.056)
Geographic Constraint Index: z-score	0.080	0.094	0.079	0.069
	(0.031)	(0.027)	(0.032)	(0.029)
Regulatory Index: z-score	0.047	0.188	0.056	0.130
	(0.024)	(0.074)	(0.021)	(0.054)
Number of Observations	206	202	206	202
Adjusted R-squared	0.787	0.716	0.807	0.787
Instrument for Land-Value Differential?	Yes	Yes	Yes	Yes
Instrument for Regulatory Index?	No	Yes	No	Yes
Elasticity of Substitution	1.000	1.000	0.583	0.456
			(0.828)	(0.453)
p-value for CRS restrictions	0.06	0.27	0.30	0.53
p-value of test of regressor exogeneity	0.08	0.02	0.33	0.00
p-value of test of overidentifying restrictions	0.66	0.18	0.00	0.00

Robust standard errors, clustered by CMSA, reported in parentheses (regressions are performed without clustering standard errors for tests of overidentifying restrictions). All specifications are constrained to have constant returns to scale. Columns 1 and 2 correspond to the specification in Table 2, Column 2; in column 1, the land-value differential is treated as endogenous and in column 2 the land-value differential and geographic constraint index are both treated as endogenous. Columns 3 and 4 correspond to the specification in Table 2, Column 4; in column 3, the land-value differential and differential squared are treated as endogenous and in column 4 the land-value differential, differential squared, and geographic constraint index are all treated as endogenous. All regressions are estimated by two-stage least squares regressions. The instrumental variables used are the inverse distance to the sea, USDA natural amenities score, their squares and interaction, the nontraditional Christian share in 1971, the share of local expenditures devoted to protective inspections in 1982, and their interactions with the inverse distance to the sea and USDA natural amenities score. Table A1 displays all first-stage regressions.

TABLE 6: INFERRED INDICES OF SELECTED METROPOLITAN AREAS, RANKED BY LOWEST HOUSING PRODUCTIVITY

	Housing Productivity (1)	Regulatory Cost Index (2)	Trade Productivity (3)	Quality of Life (4)	Total Amenity Value (5)
Metropolitan Areas:					
San Luis Obispo-Atascadero-Paso Robles, CA MSA	-0.648	0.164	0.028	0.058	-0.040
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
Los Angeles-Long Beach, CA PMSA	-0.424	0.124	0.091	0.076	0.058
Orange County, CA PMSA	-0.385	0.042	0.097	0.094	0.087
Bergen-Passaic, NJ PMSA	-0.366	0.009	0.126	0.028	0.043
Boston, MA-NH PMSA	-0.331	0.231	0.087	0.032	0.028
Washington, DC-MD-VA-WV PMSA	-0.120	0.042	0.117	0.022	0.075
New York, NY PMSA	0.026	0.018	0.151	0.098	0.199
Phoenix-Mesa, AZ MSA	0.032	0.117	-0.004	0.017	0.020
Chicago, IL PMSA	0.033	-0.086	0.049	0.005	0.042
Philadelphia, PA-NJ PMSA	0.114	-0.021	0.055	-0.011	0.045
Atlanta, GA MSA	0.184	-0.030	-0.015	-0.023	0.000
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
Houston, TX PMSA	0.314	-0.070	-0.001	-0.053	0.003
McAllen-Edinburg-Mission, TX MSA	0.627	-0.109	-0.186	-0.006	-0.012
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	0.092	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. The Regulatory Cost Index is based upon the projection of housing prices on the WRLURI subindices, and is expressed such that higher numbers indicate lower productivity. Trade productivity is calculated as 0.8 times the overall wage differential plus 0.025 times the land-value differential. Refer to section 7 of the text for the calculation of quality-of-life estimates. Quality of life and total amenity value are expressed as a fraction of average pre-tax household income.

TABLE 7: PRODUCTIVITY IN TRADEABLE AND HOUSING SECTORS ACCORDING TO METROPOLITAN POPULATION AND DENSITY

	Dependent Variable						
				Scaled Productivities			
	Trade Productivity (1)	Housing Productivity (2)	Regulatory Cost Index (3)	Trade Only (4)	Housing Only (5)	Total: Trade and Housing (6)	Total: Trade and Housing (RCI Only) (7)
Panel A: Population							
Log of Population	0.056	-0.068	0.024	0.036	-0.012	0.024	0.032
	(0.004)	(0.023)	(0.007)	(0.003)	(0.004)	(0.004)	(0.003)
Number of Observations	207	207	207	207	207	207	207
Adjusted R-squared	0.649	0.146	0.101	0.649	0.146	0.474	0.62
Panel B: Population Density							
Weighted Density Differential	0.064	-0.066	0.027	0.041	-0.012	0.029	0.036
	(0.004)	(0.030)	(0.010)	(0.003)	(0.005)	(0.004)	(0.002)
Number of Observations	207	207	207	207	207	207	207
Adjusted R-squared	0.442	0.072	0.064	0.442	0.072	0.369	0.424

Robust standard errors, clustered by CMSA, reported in parentheses. Trade and housing productivity differentials and regulatory cost index are calculated as in table 6. 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. Total productivity (RCI Only) in column 7 is defined as the traded goods share, 0.64, times trade productivity minus the housing share, 0.18, times the Regulatory Cost Index.

TABLE 8: QUALITY OF LIFE, LAND VALUES, AND HOUSING PRODUCTIVITY

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Dependent Variable: Quality of Life					
Total Housing Productivity	-0.10	0.04	0.06			
	(0.02)	(0.02)	(0.02)			
Regulatory Cost Index (RCI)				0.19	-0.01	-0.04
				(0.06)	(0.03)	(0.03)
Adjusted R-squared	0.22	0.67	0.78	0.15	0.66	0.77
Elasticity of Social Welfare (Consumption Equivalent) with Respect to Housing Productivity	0.08	0.22	0.24	-0.01	0.19	0.22
Panel B	Dependent Variable: Land Value					
Total Housing Productivity	-1.47	0.37	0.58			
	(0.27)	(0.27)	(0.33)			
Regulatory Cost Index (RCI)				2.88	0.17	-0.43
				(0.81)	(0.38)	(0.44)
Adjusted R-squared	0.24	0.64	0.78	0.17	0.63	0.78
Controls for Natural Amenties		X	X		X	X
Controls for Artificial Amenties			X			X
Number of Observations	207	204	198	207	204	198

Robust standard errors, clustered by CMSA, in parentheses. Quality of life and regulatory cost index are calculated as in table 6. Natural controls: quadratics in heating and cooling degree days, July humidity, annual sunshine, annual precipitation, adjacency to sea or lake, log inverse distance to sea, geographic constraint index, and average slope. Artificial controls include eating and drinking establishments and employment, violent crime rate, non-violent crime rate, median air quality index, teacher-student ratio, and fractions with a college degree, some college, and high-school degree. Both sets of controls are from Albouy et al. (2012) and Albouy (2016). Elasticity of Social Welfare with Respect to Housing Productivity is calculated as expenditure share of housing, 0.18, plus (minus) elasticity of Quality of Life with respect to Housing Productivity (minus RCI).

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

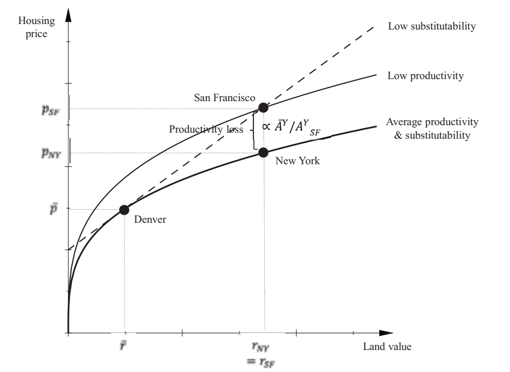


Figure 1B: The effect of low productivity or low substitutability on housing prices in logarithms

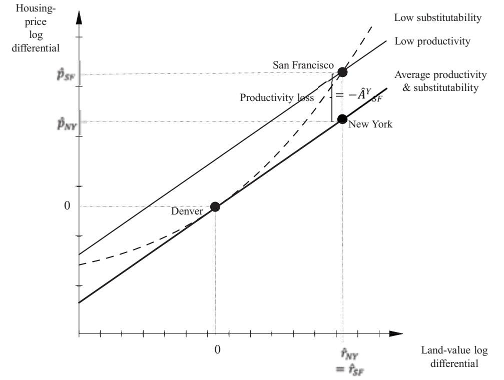


Figure 1C: Housing Prices vs. Land Values

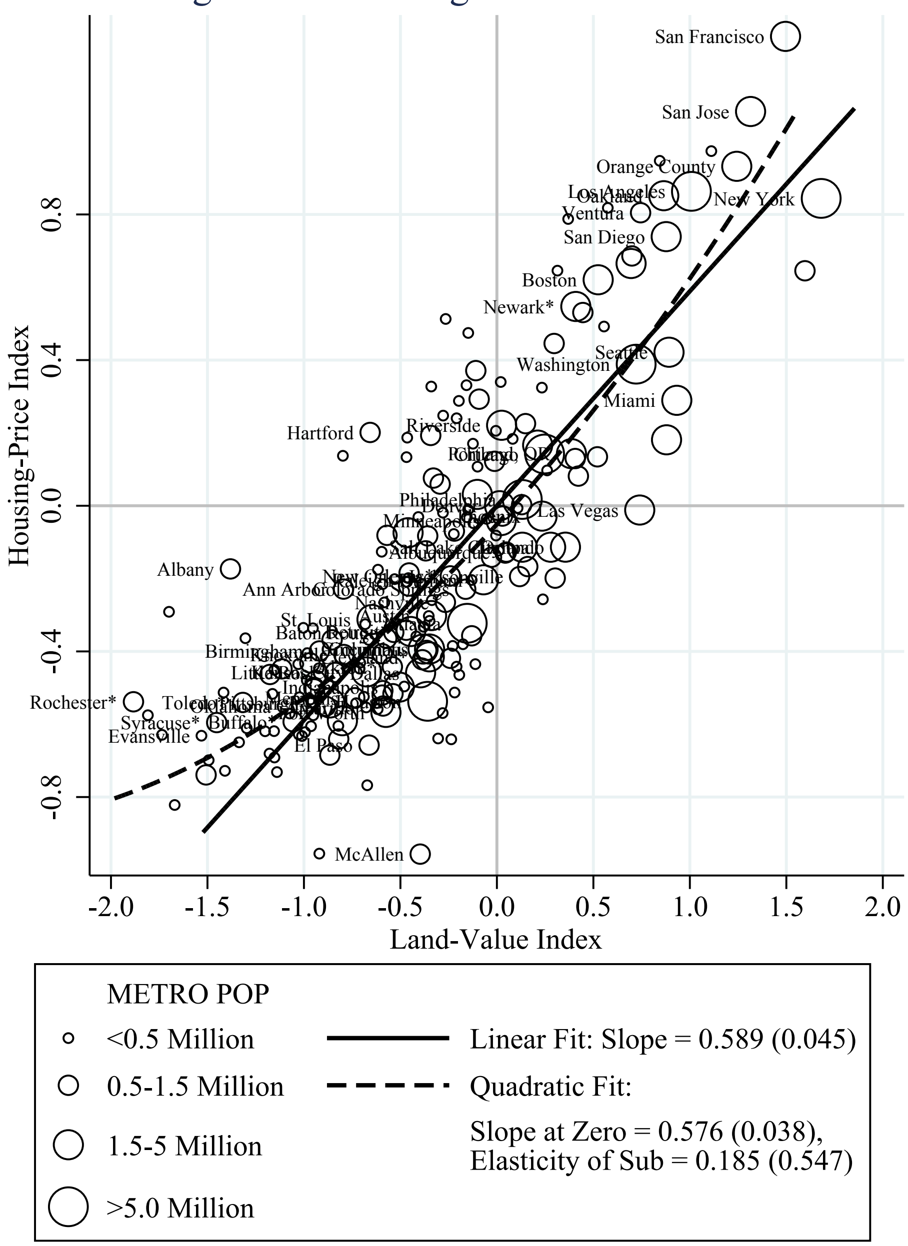


Figure 2A: Construction Prices vs. Land Values

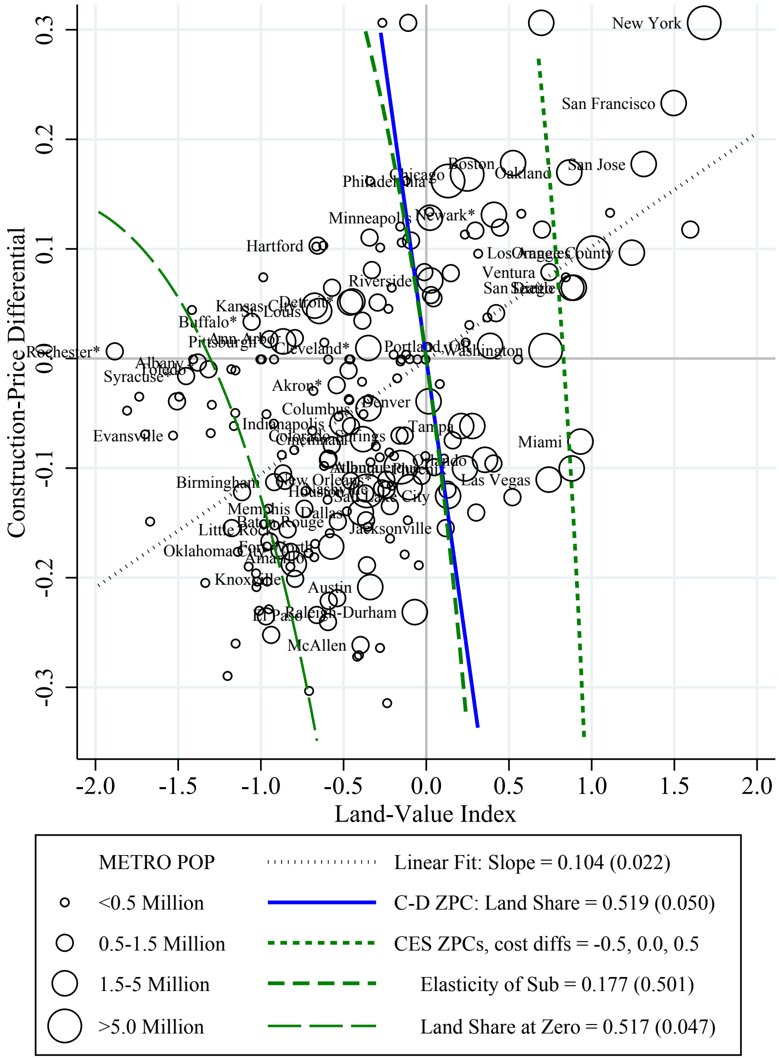


Figure 2B: Three-Dimensional Cost Curve, corresponding to ZPC Curves in Figure 2A, Estimated from Data, No Covariates

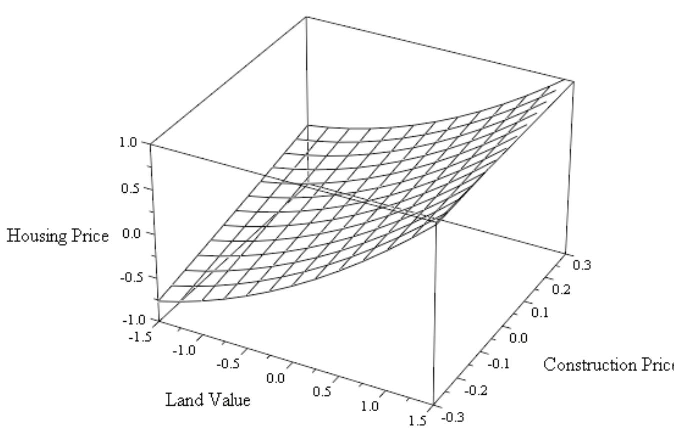


Fig. 3: Productivity in the Tradeable and Housing Sectors

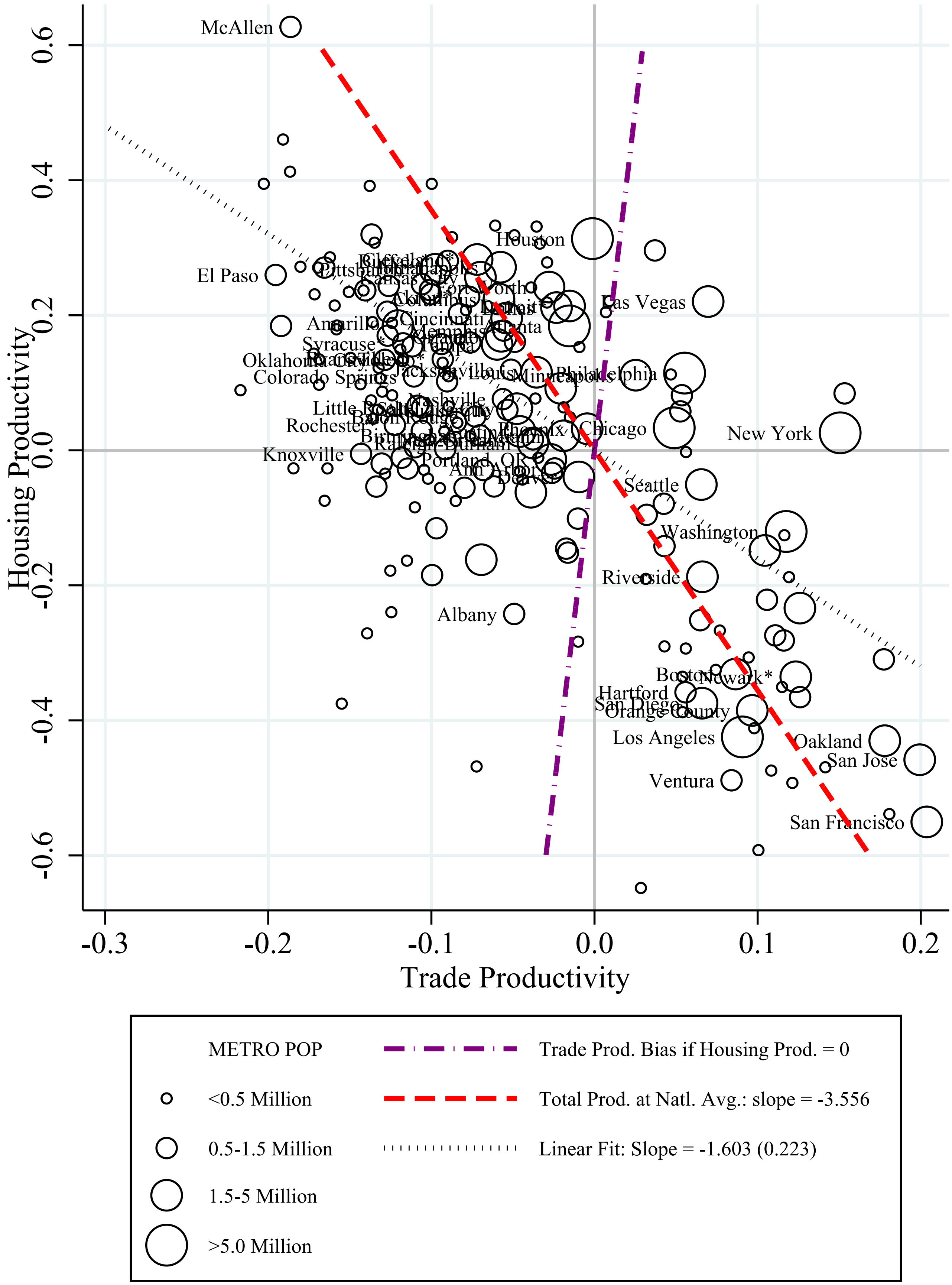


Figure 4: Regulatory Cost Index vs. Log Population Density

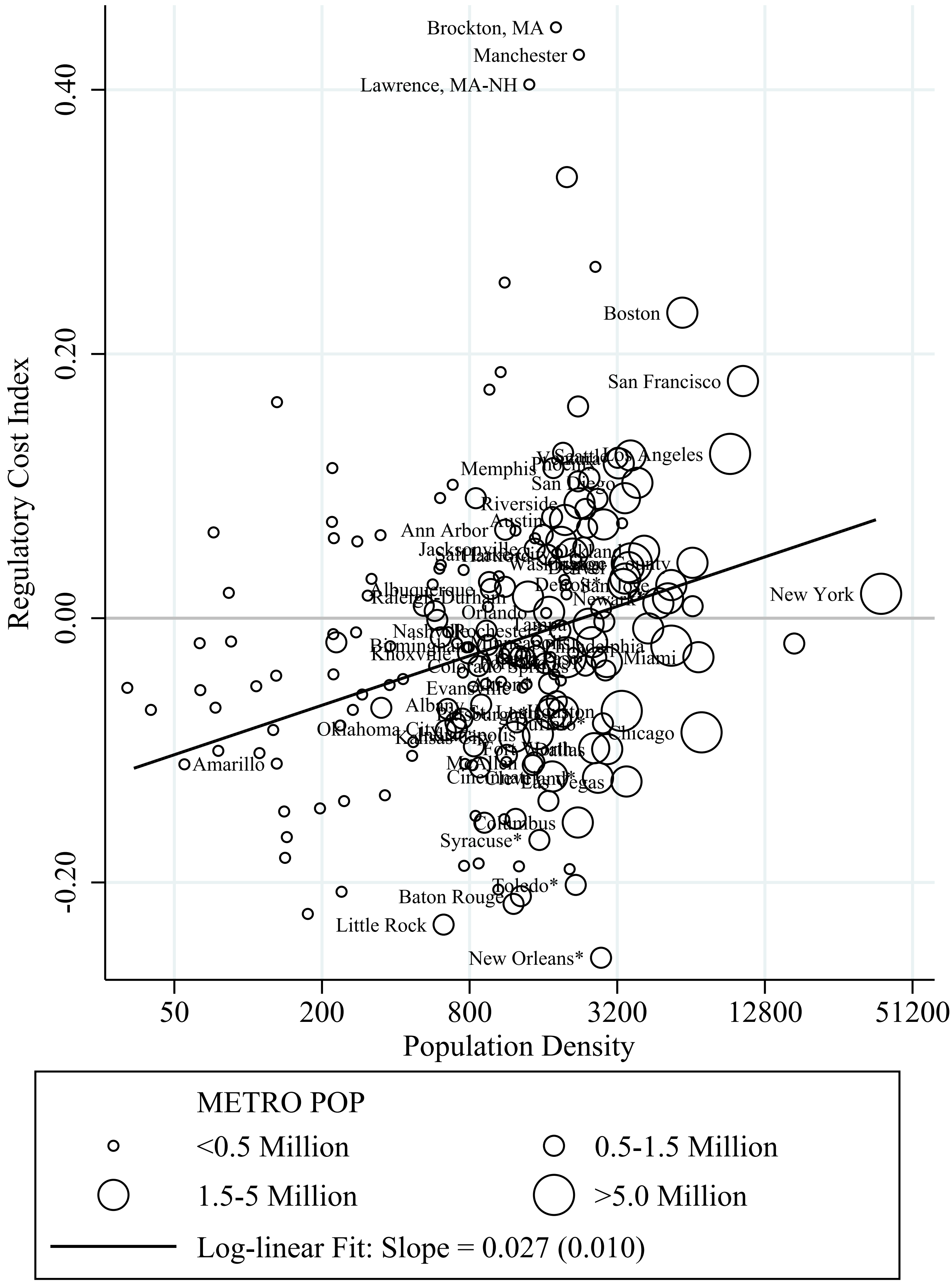
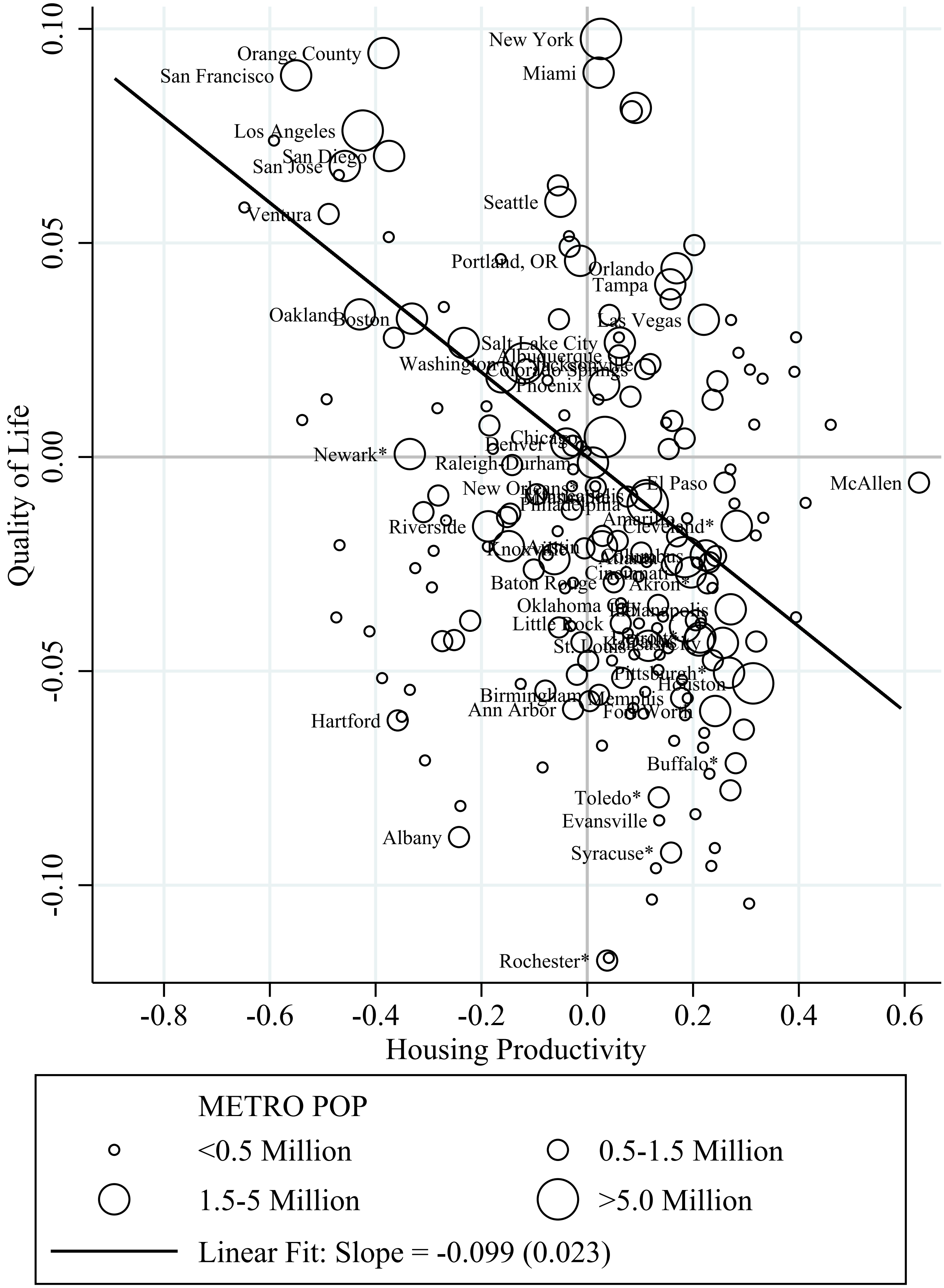


Figure 5: Quality of Life vs. Housing Productivity



Appendix for Online Publication Only

A 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 $\gamma_2 = -\gamma_3 = \zeta\phi^L(1-\phi^L)(1-\sigma^Y)$.

B Wage and Housing Price Indices

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

We regress the log hourly wage on a set of MSA dummies and a number of individual covariates, each of which is interacted with gender:

- 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 4.1, the construction price index is taken from RS Means company. For each city in the sample, RS Means reports construction costs for a composite of nine common structure types. The index reflects the costs of labor, materials, and equipment rental, but not cost variations from regulatory restrictions, restrictive union practices, or regional differences in building codes. We renormalize this index as a $z-$score with an average value of zero and a standard deviation of one across cities.[32]

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.

[32]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.

TABLE A1: INSTRUMENTAL VARIABLES ESTIMATES, FIRST-STAGE REGRESSIONS

Dependent Variable	Land Rent minus Construction Price (1)	Land Rent minus Construction Price (2)	Regulatory Index: z-score (3)	Land Rent minus Construction Price (4)	Land Rent minus Construction Price Squared (5)	Land Rent minus Construction Price (6)	Land Rent minus Construction Price Squared (7)	Regulatory Index: z-score (8)
Geographic Constraint Index: z-score	0.075	0.034	-0.081	0.095	0.016	0.100	0.023	-0.039
	(0.060)	(0.059)	(0.102)	(0.073)	(0.071)	(0.065)	(0.063)	(0.095)
Regulatory Index: z-score	0.108			0.106	-0.093			
	(0.055)			(0.047)	(0.040)			
Inverse of Mean Distance from Sea: z-score	0.280	0.287	0.120	0.240	-0.040	0.207	-0.099	0.242
	(0.053)	(0.050)	(0.087)	(0.138)	(0.103)	(0.129)	(0.119)	(0.143)
USDA Amenities Score: z-score	0.081	0.090	0.172	0.068	-0.037	0.068	-0.038	0.254
	(0.022)	(0.019)	(0.033)	(0.028)	(0.028)	(0.027)	(0.023)	(0.046)
Non-traditional Christian Share (1971): z-score		-0.055	-0.330			-0.123	-0.051	-0.559
		(0.040)	(0.080)			(0.051)	(0.052)	(0.115)
Protective Inspections Share (1980): z-score		0.104	-0.069			0.150	-0.090	-0.027
		(0.043)	(0.106)			(0.049)	(0.059)	(0.079)
Inverse of Mean Distance from Sea: z-score squared				0.008	0.101	-0.029	0.117	-0.175
				(0.041)	(0.029)	(0.043)	(0.040)	(0.053)
USDA Amenities Score: z-score squared				0.007	0.025	0.004	0.017	-0.031
				(0.005)	(0.006)	(0.006)	(0.008)	(0.013)
Inverse of Mean Distance from Sea: z-score times USDA Amenities Score: z-score				-0.035	0.008	-0.026	0.001	0.016
				(0.009)	(0.010)	(0.012)	(0.014)	(0.025)
Inverse of Mean Distance from Sea: z-score times Non-traditional Christian Share (1971): z-score						-0.169	0.012	-0.372
						(0.077)	(0.061)	(0.158)
USDA Amenities Score: z-score times Non-traditional Christian Share (1971): z-score						-0.038	-0.026	0.034
						(0.026)	(0.028)	(0.054)
Inverse of Mean Distance from Sea: z-score times Protective Inspections Share (1980): z-score						-0.005	0.044	0.103
						(0.055)	(0.064)	(0.098)
USDA Amenities Score: z-score times Protective Inspections Share (1980): z-score						-0.035	0.048	-0.071
						(0.018)	(0.023)	(0.036)
Number of Observations	206	202	202	206	206	202	202	202
Adjusted R-squared	0.576	0.579	0.254	0.587	0.301	0.628	0.324	0.343
F-statistic of Excluded Instruments	15.2	18.9	16.0	31.1	18.0	52.8	38.1	12.7
First Stage Regression for	Table 5 Column 1	Table 5 Column 2	Table 5 Column 2	Table 5 Column 3	Table 5 Column 3	Table 5 Column 4	Table 5 Column 4	Table 5 Column 4

Robust standard errors, clustered by CMSA, reported in parentheses. See Table 5 for variable descriptions and data sources.

TABLE A2: LIST OF METROPOLITAN INDICES RANKED BY HOUSING PRICE DIFFERENTIAL, 2005-2010

			Adjusted Differentials					*Raw Differentials*			*Productivity*			
Full Name	Population	Census Division	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	Regulatory Cost Index	Housing Price Rank
Metropolitan Areas:														
San Francisco, CA PMSA	1,785,097	9	1.496	1.416	1.289	0.207	0.214	1.684	2.169	0.233	-0.550	0.204	0.180	1
San Jose, CA PMSA	1,784,642	9	1.315	1.273	1.083	0.207	0.214	-0.107	1.710	0.177	-0.458	0.199	0.025	2
Stamford-Norwalk, CT PMSA	361,024	1	1.111	1.020	0.974	0.157	0.243	-0.624	0.561	0.133	-0.469	0.141	0.018	3
Santa Barbara-Santa Maria-Lompoc, CA MSA	407,057	9	0.844	0.746	0.947	0.073	-0.066	0.542	2.802	0.074	-0.592	0.100	0.058	4
Orange County, CA PMSA	3,026,786	9	1.243	1.192	0.932	0.087	0.115	0.026	1.153	0.097	-0.385	0.097	0.042	5
Los Angeles-Long Beach, CA PMSA	9,848,011	9	1.008	0.961	0.863	0.087	0.115	0.841	1.153	0.097	-0.424	0.091	0.124	6
Oakland, CA PMSA	2,532,756	9	0.865	0.781	0.851	0.192	0.186	0.543	1.605	0.170	-0.430	0.178	0.051	7
New York, NY PMSA	9,747,281	2	1.681	1.546	0.844	0.152	0.247	-0.221	0.561	0.306	0.026	0.151	0.018	8
Santa Rosa, CA PMSA	472,102	9	0.575	0.584	0.818	0.207	0.214	1.285	1.671	0.132	-0.539	0.181	0.173	9
Ventura, CA PMSA	802,983	9	0.745	0.757	0.805	0.086	0.115	1.668	2.489	0.079	-0.489	0.084	0.121	10
San Luis Obispo-Atascadero-Paso Robles, CA MSA	266,971	9	0.369	0.267	0.787	0.003	-0.112	1.399	1.810	0.037	-0.648	0.028	0.164	11
San Diego, CA MSA	3,053,793	9	0.877	0.878	0.739	0.061	0.093	0.946	1.691	0.065	-0.375	0.066	0.102	12
Bergen-Passaic, NJ PMSA	1,387,028	2	0.700	0.652	0.686	0.152	0.247	0.317	0.561	0.118	-0.366	0.126	0.009	13
Nassau-Suffolk, NY PMSA	2,875,904	2	0.695	0.663	0.665	0.152	0.247	0.811	0.561	0.306	-0.234	0.126	-0.008	14
Salinas, CA MSA	410,370	9	0.314	0.238	0.646	0.113	-0.035	-0.074	1.824	0.096	-0.493	0.121	0.072	15
Jersey City, NJ PMSA	597,924	2	1.596	1.457	0.645	0.159	0.262	-0.594	0.236	0.118	0.084	0.153	-0.019	16
Boston, MA-NH PMSA	3,552,421	1	0.525	0.497	0.621	0.093	0.101	1.264	0.241	0.178	-0.331	0.087	0.231	17
Newark, NJ PMSA	2,045,344	2	0.409	0.357	0.547	0.159	0.262	0.005	0.073	0.131	-0.335	0.123	0.015	18
Vallejo-Fairfield-Napa, CA PMSA	541,884	9	0.445	0.465	0.531	0.207	0.214	0.853	0.990	0.119	-0.310	0.177	0.091	19
Danbury, CT PMSA	223,095	1	-0.266	-0.336	0.513	0.149	0.255	-0.586	0.561	0.306	-0.412	0.098	0.101	20
Naples, FL MSA	318,537	5	0.555	0.572	0.492	0.008	-0.213	0.125	2.291	-0.001		0.052		21
Bridgeport, CT PMSA	470,094	1	-0.149	-0.253	0.475	0.157	0.254	0.304	0.561	0.106	-0.474	0.108	0.017	22
Middlesex-Somerset-Hunterdon, NJ PMSA	1,247,641	2	0.297	0.277	0.446	0.152	0.247	2.182	0.561	0.117	-0.282	0.116	0.069	23
Seattle-Bellevue-Everett, WA PMSA	2,692,066	9	0.892	0.848	0.422	0.051	0.035	1.642	0.719	0.065	-0.051	0.065	0.123	24
Washington, DC-MD-VA-WV PMSA	5,650,154	5	0.722	0.728	0.389	0.132	0.177	0.850	-0.741	0.008	-0.120	0.117	0.042	25
Monmouth-Ocean, NJ PMSA	1,217,783	2	-0.109	-0.122	0.371	0.152	0.247	2.067	0.561	0.306	-0.221	0.106	0.077	26
Lawrence, MA-NH PMSA	413,626	1	0.020	-0.028	0.340	0.099	0.121	1.811	0.241	0.134	-0.267	0.077	0.404	27
Brockton, MA PMSA	268,092	1	-0.158	-0.170	0.331	0.097	0.096	2.833	0.241	0.120	-0.325	0.074	0.447	28
Dutchess County, NY PMSA	293,562	2	-0.340	-0.304	0.327	0.170	0.262	0.169	0.561	0.162	-0.351	0.115	-0.019	29
Trenton, NJ PMSA	366,222	2	0.233	0.258	0.324	0.159	0.262	1.712	-0.847	0.113	-0.188	0.119	0.045	30
New Haven-Meriden, CT PMSA	558,692	1	-0.092	-0.135	0.293	0.159	0.262	-0.636	0.786	0.108	-0.274	0.111	-0.003	31
Miami, FL PMSA	2,500,625	5	0.932	0.909	0.289	-0.057	-0.081	0.662	2.341	-0.076	0.021	-0.019	-0.030	32
Medford-Ashland, OR MSA	201,286	9	-0.197	-0.338	0.288	-0.164	-0.046	0.874	2.003	0.003	-0.375	-0.155	0.065	33
Atlantic-Cape May, NJ PMSA	367,803	2	-0.278	-0.307	0.248	0.074	0.055	0.284	1.778	0.101	-0.294	0.056	0.026	34
Bremerton, WA PMSA	240,862	9	-0.209	-0.249	0.240	0.060	0.063	0.026	1.124	0.065	-0.290	0.043	0.040	35
Stockton-Lodi, CA MSA	674,860	9	0.148	0.128	0.226	0.067	0.165	0.099	-0.834	0.078	-0.142	0.043	0.090	36
Riverside-San Bernardino, CA PMSA	4,143,113	9	0.024	0.054	0.221	0.087	0.115	0.599	0.437	0.071	-0.187	0.066	0.087	37
Boulder-Longmont, CO PMSA	311,786	8	-0.005	0.001	0.206	-0.010	0.003	4.034	0.695	-0.089	-0.283	-0.010	0.254	38
Hartford, CT MSA	1,231,125	1	-0.657	-0.664	0.201	0.090	0.091	0.293	-0.281	0.103	-0.358	0.056	0.048	39
Worcester, MA-CT PMSA	547,274	1	-0.343	-0.359	0.193	0.093	0.101	2.406	0.241	0.110	-0.252	0.065	0.334	40
Portsmouth-Rochester, NH-ME PMSA	262,128	1	-0.465	-0.545	0.187	0.095	0.171	0.994	0.241	-0.038	-0.388	0.054	0.266	41
Reno, NV MSA	414,820	8	0.082	0.087	0.184	0.003	-0.178	-0.486	1.328	-0.023	-0.190	0.031	-0.029	42
Fort Lauderdale, FL PMSA	1,766,476	5	0.879	0.863	0.181	-0.057	-0.082	0.890	2.295	-0.100	0.092	-0.021	0.011	43
Newburgh, NY-PA PMSA	444,061	2	-0.124	-0.120	0.170	0.166	0.265	-0.538	0.047	0.162	-0.126	0.116	-0.104	44
Baltimore, MD PMSA	2,690,886	5	0.211	0.212	0.167	0.131	0.177	-0.661	-0.351	-0.062	-0.148	0.104	0.091	45
Portland-Vancouver, OR-WA PMSA	2,230,947	9	0.386	0.361	0.143	-0.049	-0.071	-0.038	0.419	0.012	-0.014	-0.027	-0.033	46
Chicago, IL PMSA	8,710,824	3	0.247	0.259	0.142	0.054	0.058	-0.603	0.541	0.168	0.033	0.049	-0.086	47
Portland, ME MSA	256,178	1	-0.798	-0.881	0.137	-0.079	-0.156	0.846	1.005	-0.084	-0.468	-0.072	0.186	48
West Palm Beach-Boca Raton, FL MSA	1,279,950	5	0.521	0.419	0.134	-0.033	0.046	0.309	1.720	-0.127	-0.033	-0.026	-0.040	49
Manchester, NH PMSA	212,326	1	-0.468	-0.537	0.134	0.095	0.171	2.615	0.241	-0.037	-0.335	0.054	0.426	50
Sarasota-Bradenton, FL MSA	688,126	5	0.406	0.420	0.130	-0.103	-0.061	1.529	1.849	-0.096	-0.056	-0.080	0.063	51
Modesto, CA MSA	510,385	9	-0.012	-0.028	0.122	0.041	0.044	-0.211	-0.724	0.079	-0.095	0.032	0.007	52
Eugene-Springfield, OR MSA	351,109	9	-0.100	-0.173	0.107	-0.154	-0.239	0.152	1.647	-0.001	-0.163	-0.115	-0.042	53
Olympia, WA PMSA	250,979	9	0.260	0.245	0.097	0.060	0.054	0.626	0.466	0.031	-0.003	0.056	0.066	54
Tacoma, WA PMSA	796,836	9	0.422	0.414	0.081	0.050	0.033	-0.214	0.377	0.041	0.082	0.054	0.083	55
Fresno, CA MSA	1,063,899	9	-0.329	-0.304	0.076	-0.013	-0.034	1.181	-0.793	0.081	-0.151	-0.016	0.160	56
Springfield, MA MSA*	609,993	1	-0.294	-0.362	0.060	-0.011	-0.007	0.056	-0.095	0.051	-0.146	-0.017	0.125	57
Norfolk-Virginia Beach-Newport News, VA- MSA	1,667,410	5	-0.101	-0.092	0.031	-0.078	-0.053	-0.222	1.512	-0.117	-0.162	-0.069	0.058	58
Philadelphia, PA-NJ PMSA	5,332,822	2	0.132	0.146	0.017	0.062	0.045	0.644	-0.927	0.162	0.114	0.055	-0.021	59
Fort Myers-Cape Coral, FL MSA	586,908	5	0.128	0.140	0.003	-0.078	-0.071	-0.553	1.187	-0.120	-0.054	-0.062	-0.103	60

TABLE A2: LIST OF METROPOLITAN INDICES RANKED BY HOUSING PRICE DIFFERENTIAL, 2005-2010

			Adjusted Differentials					*Raw Differentials*			*Productivity*			
Full Name	Population	Census Division	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	Regulatory Cost Index	Housing Price Rank
Denver, CO PMSA	2,445,781	8	0.014	0.000	0.000	-0.010	0.003	1.299	-0.604	-0.039	-0.039	-0.010	0.039	61
Grand Junction, CO MSA	146,093	8	0.107	0.045	-0.006	-0.146	-0.060	0.457	0.702	-0.091	-0.035	-0.128	-0.019	62
Merced, CA MSA	245,321	9	-0.149	-0.139	-0.011	-0.005	0.255	0.603	-0.927	-0.001		-0.046		63
Las Vegas, NV-AZ MSA	2,141,893	8	0.740	0.756	-0.012	0.044	-0.063	-1.524	0.150	-0.110	0.220	0.070	-0.124	64
Asheville, NC MSA	251,894	5	-0.280	-0.302	-0.019	-0.174	-0.229	0.097	1.891	-0.264	-0.271	-0.139	-0.021	65
Wilmington-Newark, DE-MD PMSA	635,430	5	0.028	0.051	-0.028	0.062	0.045	0.706	-0.705	0.058	0.058	0.053	0.104	66
Phoenix-Mesa, AZ MSA	4,364,094	8	0.234	0.296	-0.028	-0.013	-0.014	0.962	-0.741	-0.100	0.032	-0.004	0.117	67
Hagerstown, MD PMSA	145,910	5	-0.407	-0.403	-0.031	0.136	0.171	0.137	-0.505	-0.271	-0.307	0.094	0.030	68
Madison, WI MSA	491,357	3	-0.156	-0.150	-0.032	-0.070	-0.180	0.326	-0.869	-0.003	-0.043	-0.044	0.049	69
Visalia-Tulare-Porterville, CA MSA	429,668	9	-0.053	-0.162	-0.036	-0.016	-0.019	0.322	-0.471	-0.001		-0.014		70
Minneapolis-St. Paul, MN-WI MSA	3,269,814	4	0.022	0.012	-0.041	0.024	-0.011	0.104	-0.481	0.128	0.111	0.025	-0.018	71
Salem, OR PMSA	396,103	9	-0.122	-0.182	-0.048	-0.042	-0.063	0.580	0.199	0.003	-0.011	-0.034	0.004	72
Tucson, AZ MSA	1,020,200	8	-0.220	-0.230	-0.070	-0.123	-0.178	0.200	-0.292	-0.135	-0.115	-0.097	0.106	73
Milwaukee-Waukesha, WI PMSA	1,559,667	3	-0.460	-0.445	-0.074	-0.031	-0.015	-0.514	0.628	0.051	-0.062	-0.039	0.030	74
Fort Collins-Loveland, CO MSA	298,382	8	-0.223	-0.216	-0.078	-0.116	-0.216	0.831	0.110	-0.086	-0.075	-0.085	-0.017	75
Bakersfield, CA MSA	807,407	9	-0.570	-0.604	-0.081	0.044	-0.102	-0.373	-0.236	0.065	-0.079	0.042	0.024	76
Fort Pierce-Port St. Lucie, FL MSA	406,296	5	-0.004	-0.017	-0.082	-0.075	-0.191	0.298	1.765	-0.001		-0.044		77
Charleston-North Charleston, SC MSA	659,191	5	-0.359	-0.352	-0.083	-0.111	-0.107	-1.255	1.545	-0.189	-0.185	-0.100	-0.085	78
Orlando, FL MSA	2,082,421	5	0.355	0.382	-0.114	-0.088	-0.121	0.079	0.350	-0.092	0.169	-0.057	0.005	79
Tampa-St. Petersburg-Clearwater, FL MSA	2,747,272	5	0.278	0.288	-0.114	-0.091	-0.140	-0.050	0.621	-0.062	0.157	-0.060	-0.004	80
Salt Lake City-Ogden, UT MSA	1,567,650	8	0.132	0.104	-0.114	-0.078	-0.159	-0.509	2.113	-0.125	0.062	-0.048	0.049	81
Kenosha, WI PMSA	165,382	3	0.009	0.041	-0.123	0.059	0.068	1.833	0.929	0.011	0.112	0.047	0.091	82
Richmond-Petersburg, VA MSA	1,119,459	5	-0.369	-0.354	-0.124	-0.012	-0.072	-0.859	-0.993	-0.123	-0.101	-0.010	-0.026	83
Gainesville, FL MSA	243,574	5	-0.597	-0.637	-0.126	-0.148	-0.215	-0.237	-0.669	-0.129	-0.178	-0.125	-0.048	84
Albuquerque, NM MSA	841,428	8	0.049	0.020	-0.127	-0.087	-0.195	0.957	-0.854	-0.099	0.060	-0.053	0.022	85
Allentown-Bethlehem-Easton, PA MSA	706,374	2	0.043	0.037	-0.130	-0.040	0.079	0.412	-0.401	0.055	0.161	-0.049	-0.077	86
Daytona Beach, FL MSA	587,512	5	-0.028	-0.022	-0.141	-0.135	-0.303	-0.845	1.549	-0.107	0.042	-0.085	-0.076	87
Melbourne-Titusville-Palm Bay, FL MSA	536,357	5	0.160	0.189	-0.167	-0.112	-0.065	0.352	1.732	-0.075	0.157	-0.094	0.005	88
Albany-Schenectady-Troy, NY MSA	906,208	2	-1.381	-1.369	-0.173	-0.026	-0.067	-0.241	-0.279	-0.004	-0.242	-0.049	-0.065	89
Racine, WI PMSA	200,601	3	-0.616	-0.597	-0.176	-0.028	0.024	-1.338	1.233	0.015	-0.031	-0.046	0.037	90
Lancaster, PA MSA	507,766	2	-0.455	-0.451	-0.185	-0.083	-0.154	0.030	-0.841	-0.062	-0.029	-0.068	-0.113	91
New Orleans, LA MSA*	1,211,035	7	-0.241	-0.292	-0.193	-0.057	-0.156	-2.433	2.255	-0.110	0.016	-0.038	-0.257	92
Jacksonville, FL MSA	1,301,808	5	0.118	0.139	-0.194	-0.076	-0.130	0.702	0.900	-0.155	0.119	-0.051	0.053	93
Fort Walton Beach, FL MSA	178,473	5	-0.459	-0.595	-0.199	-0.152	0.283	-0.523	1.457	-0.001		-0.200		94
Provo-Orem, UT MSA	545,307	8	0.302	0.265	-0.199	-0.128	-0.217	-0.573	1.503	-0.141	0.202	-0.083	0.054	95
Spokane, WA MSA	468,684	9	-0.530	-0.578	-0.202	-0.118	-0.148	0.755	-0.082	-0.053	-0.029	-0.104	0.025	96
Raleigh-Durham-Chapel Hill, NC MSA	1,589,388	5	-0.069	-0.060	-0.203	-0.042	-0.033	1.107	-1.027	-0.231	0.011	-0.038	0.016	97
Savannah, GA MSA	343,092	5	-0.131	-0.144	-0.204	-0.102	-0.168	-0.280	1.528	-0.179	0.021	-0.076	0.009	98
Myrtle Beach, SC MSA	263,868	5	-0.466	-0.493	-0.209	-0.185	-0.128	-1.005	1.614	-0.001		-0.170		99
York, PA MSA	428,937	2	-0.388	-0.383	-0.215	-0.022	-0.107	0.836	-0.831	-0.021	0.049	-0.015	-0.022	100
Yuba City, CA MSA	165,539	9	-0.592	-0.735	-0.215	0.012	-0.066	-0.769	-0.743	-0.001		0.006		101
Boise City, ID MSA	571,271	8	-0.458	-0.461	-0.220	-0.136	-0.186	-1.095	0.361	-0.112	-0.027	-0.114	-0.066	102
Ann Arbor, MI PMSA*	630,518	3	-0.795	-0.762	-0.229	-0.010	-0.036	1.235	-0.949	0.019	-0.027	-0.024	0.067	103
Colorado Springs, CO MSA	604,542	8	-0.162	-0.198	-0.229	-0.134	-0.150	0.239	-0.331	-0.070	0.109	-0.111	-0.036	104
Reading, PA MSA	407,125	2	0.238	0.246	-0.257	-0.050	-0.046	0.658	-0.616	0.015	0.331	-0.036	-0.052	105
Billings, MT MSA	144,797	8	-0.337	-0.383	-0.259	-0.198	-0.441	-0.616	-0.868	-0.095	0.060	-0.133	-0.111	106
Nashville, TN MSA	1,495,419	6	-0.267	-0.252	-0.265	-0.066	-0.095	-1.132	-0.795	-0.119	0.076	-0.056	-0.009	107
Roanoke, VA MSA	243,506	5	-0.584	-0.641	-0.265	-0.105	-0.138	-1.335	0.513	-0.160	-0.056	-0.095	-0.027	108
Glens Falls, NY MSA	128,774	2	-1.699	-1.681	-0.291	-0.131	-0.292	-2.636	0.583	-0.069	-0.240	-0.125	-0.100	109
Austin-San Marcos, TX MSA	1,705,075	7	-0.339	-0.295	-0.302	-0.049	-0.069	1.035	-1.241	-0.209	0.028	-0.046	0.074	110
Greeley, CO PMSA	254,759	8	-0.353	-0.303	-0.303	-0.010	0.002	-0.696	-0.930	-0.154	0.064	-0.019	-0.054	111
St. Louis, MO-IL MSA	2,733,694	4	-0.648	-0.638	-0.312	-0.039	-0.126	-1.636	-0.881	0.043	0.116	-0.036	-0.071	112
Richland-Kennewick-Pasco, WA MSA	245,649	9	-0.349	-0.397	-0.316	0.022	0.146	0.789	-0.823	-0.037	0.153	-0.009	0.019	113
Atlanta, GA MSA	5,315,841	5	-0.154	-0.113	-0.323	-0.007	0.033	0.028	-1.225	-0.099	0.184	-0.015	-0.030	114
Green Bay, WI MSA	247,319	3	-0.683	-0.700	-0.325	-0.076	-0.005	-0.477	-0.282	-0.030	0.065	-0.089	-0.027	115
La Crosse, WI-MN MSA	132,923	3	-0.380	-0.435	-0.333	-0.154	-0.258	-0.464	0.333	-0.051	0.149	-0.119	0.073	116
Benton Harbor, MI MSA*	160,472	3	-1.003	-1.120	-0.335	-0.142	0.075	-1.155	1.040	-0.001		-0.173		117
Pensacola, FL MSA	455,102	5	-0.954	-0.980	-0.336	-0.173	-0.162	-1.566	1.158	-0.137	-0.075	-0.165	-0.187	118
Harrisburg-Lebanon-Carlisle, PA MSA	667,425	2	-0.470	-0.451	-0.342	-0.068	-0.006	0.597	-0.245	-0.011	0.160	-0.076	-0.036	119
Detroit, MI PMSA*	4,373,040	3	-0.447	-0.442	-0.345	-0.010	-0.037	-0.309	-0.221	0.052	0.214	-0.015	0.026	120
Baton Rouge, LA MSA	685,419	7	-0.535	-0.548	-0.348	-0.069	-0.044	-1.582	0.222	-0.149	0.050	-0.073	-0.210	121
Lakeland-Winter Haven, FL MSA	583,403	5	-0.130	-0.080	-0.357	-0.138	-0.201	0.337	0.156	-0.070	0.246	-0.106	0.009	122

TABLE A2: LIST OF METROPOLITAN INDICES RANKED BY HOUSING PRICE DIFFERENTIAL, 2005-2010

			Adjusted Differentials					*Raw Differentials*			*Productivity*			
Full Name	Population	Census Division	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	Regulatory Cost Index	Housing Price Rank
Fayetteville-Springdale-Rogers, AR MSA	425,685	7	-0.418	-0.410	-0.359	-0.118	-0.152	-0.688	-0.004	-0.272	0.015	-0.101	-0.207	123
Appleton-Oshkosh-Neenah, WI MSA	385,264	3	-1.303	-1.294	-0.364	-0.090	-0.058	-0.434	-0.544	-0.068	-0.084	-0.110	-0.011	124
Louisville, KY-IN MSA	1,099,588	6	-0.571	-0.592	-0.364	-0.101	-0.141	-1.193	-0.802	-0.079	0.102	-0.090	-0.138	125
Des Moines, IA MSA	536,664	4	-0.854	-0.855	-0.368	-0.079	-0.036	-1.546	-1.123	-0.112	0.002	-0.091	-0.111	126
St. Cloud, MN MSA	189,148	4	-0.665	-0.818	-0.368	-0.113	-0.313	-0.463	-0.414	0.102	0.207	-0.079	-0.051	127
Janesville-Beloit, WI MSA	160,155	3	-0.176	-0.255	-0.380	-0.172	-0.046	-0.764	-1.190	-0.018	0.286	-0.162	-0.012	128
Champaign-Urbana, IL MSA	195,671	3	-0.229	-0.273	-0.385	-0.130	-0.289	-0.900	-1.355	0.045	0.316	-0.087	-0.144	129
Columbus, OH MSA	1,718,303	3	-0.349	-0.319	-0.393	-0.058	-0.040	0.165	-1.303	-0.045	0.224	-0.059	-0.155	130
Cincinnati, OH-KY-IN PMSA	1,776,911	3	-0.383	-0.366	-0.394	-0.052	-0.040	-1.092	-0.920	-0.074	0.196	-0.054	-0.120	131
Chattanooga, TN-GA MSA	510,388	6	-0.364	-0.373	-0.397	-0.141	-0.219	-1.395	-0.157	-0.148	0.154	-0.112	-0.015	132
Birmingham, AL MSA	997,770	6	-0.920	-0.943	-0.399	-0.071	-0.141	-0.476	-0.720	-0.113	0.022	-0.070	-0.020	133
Lynchburg, VA MSA	232,895	5	-0.982	-1.045	-0.405	-0.168	-0.147	-0.984	-0.329	-0.151	-0.027	-0.164	-0.043	134
Greensboro--Winston Salem--High Point, NC MSA	1,416,374	5	-0.594	-0.590	-0.406	-0.124	-0.190	-0.815	-1.273	-0.240	0.029	-0.106	0.027	135
Knoxville, TN MSA	785,490	6	-0.793	-0.779	-0.409	-0.156	-0.175	-0.928	0.468	-0.201	-0.005	-0.143	-0.027	136
Cleveland-Lorain-Elyria, OH PMSA*	2,192,053	3	-0.350	-0.340	-0.415	-0.084	-0.115	-0.765	0.565	0.010	0.283	-0.072	-0.121	137
Lexington, KY MSA	554,107	6	-0.241	-0.303	-0.419	-0.156	-0.100	-0.153	-1.136	-0.120	0.237	-0.141	-0.030	138
Gary, IN PMSA	657,809	3	-0.386	-0.412	-0.423	0.060	0.068	-1.469	0.124	0.035	0.296	0.037	-0.029	139
Hickory-Morganton-Lenoir, NC MSA	365,364	5	-0.708	-0.687	-0.431	-0.201	-0.171	-0.979	-0.395	-0.303	-0.027	-0.185	-0.069	140
Columbia, SC MSA	627,630	5	-0.969	-0.983	-0.431	-0.136	-0.141	-1.177	-0.678	-0.235	-0.054	-0.134	-0.001	141
Huntsville, AL MSA	406,316	6	-0.112	-0.115	-0.435	-0.055	-0.177	-2.387	-0.230	-0.148	0.278	-0.029	-0.011	142
Bryan-College Station, TX MSA	179,992	7	-1.029	-1.058	-0.435	-0.178	-0.634	0.314	-1.110	-0.196	-0.042	-0.102	0.017	143
Lincoln, NE MSA	281,531	4	-0.209	-0.264	-0.442	-0.212	-0.189	0.750	-1.348	-0.116	0.272	-0.180	0.063	144
Akron, OH PMSA*	699,935	3	-0.542	-0.523	-0.442	-0.084	-0.114	-0.080	-1.109	-0.024	0.227	-0.077	-0.050	145
Wausau, WI MSA	131,612	3	-0.923	-1.013	-0.446	-0.132	-0.040	-0.731	-0.843	-0.059	0.098	-0.143	-0.018	146
Biloxi-Gulfport-Pascagoula, MS MSA	355,075	6	-0.712	-0.779	-0.447	-0.127	-0.019	-1.198	1.134	-0.178	0.074	-0.137	-0.081	147
Grand Rapids-Muskegon-Holland, MI MSA	1,157,672	3	-1.114	-1.144	-0.448	-0.113	-0.176	-0.522	-0.970	-0.122	0.005	-0.110	-0.029	148
Lansing-East Lansing, MI MSA	453,603	3	-1.154	-1.164	-0.451	-0.112	-0.083	-0.613	-1.089	-0.011	0.081	-0.124	0.032	149
Kansas City, MO-KS MSA	2,005,888	4	-0.675	-0.657	-0.456	-0.068	-0.086	-1.452	-1.140	0.048	0.256	-0.070	-0.090	150
Little Rock-North Little Rock, AR MSA	657,416	7	-0.838	-0.849	-0.458	-0.116	-0.181	-1.894	-0.752	-0.156	0.063	-0.106	-0.232	151
Dallas, TX PMSA	4,399,895	7	-0.395	-0.381	-0.459	-0.014	0.000	-0.728	-0.976	-0.141	0.211	-0.023	-0.099	152
Mobile, AL MSA	591,599	6	-1.176	-1.186	-0.463	-0.147	-0.272	-2.767	0.015	-0.155	-0.020	-0.131	-0.079	153
Hamilton-Middletown, OH PMSA	363,184	3	-0.195	-0.172	-0.465	-0.052	-0.040	-0.641	-1.083	-0.089	0.318	-0.049	-0.186	154
Duluth-Superior, MN-WI MSA*	242,041	4	-0.985	-1.046	-0.480	-0.149	-0.058	-0.923	0.266	0.074	0.214	-0.159	-0.053	155
Greenville-Spartanburg-Anderson, SC MSA	1,096,009	5	-0.938	-0.923	-0.480	-0.126	-0.174	-1.647	-0.794	-0.252	-0.011	-0.118	-0.069	156
Cedar Rapids, IA MSA	209,226	4	-0.874	-0.946	-0.488	-0.124	-0.159	-1.435	-1.252	-0.088	0.132	-0.118	-0.058	157
Galveston-Texas City, TX PMSA	286,814	7	-0.480	-0.498	-0.496	0.032	0.063	0.349	2.266	-0.139	0.221	0.009	-0.041	158
Indianapolis, IN MSA	1,823,690	3	-0.506	-0.514	-0.498	-0.065	-0.119	-1.804	-1.355	-0.059	0.271	-0.058	-0.088	159
Augusta-Aiken, GA-SC MSA	516,357	5	-0.948	-0.971	-0.499	-0.104	-0.102	-1.687	-0.913	-0.167	0.066	-0.108	-0.068	160
Scranton--Wilkes-Barre--Hazleton, PA MSA*	614,565	2	-0.948	-1.006	-0.503	-0.147	-0.257	-0.495	-0.011	0.018	0.205	-0.127	-0.097	161
Dayton-Springfield, OH MSA*	933,312	3	-0.591	-0.613	-0.508	-0.119	-0.193	-1.553	-1.375	-0.091	0.231	-0.100	-0.216	162
Peoria-Pekin, IL MSA*	357,144	3	-1.417	-1.447	-0.513	-0.060	0.003	-0.588	-1.181	0.044	0.130	-0.093	-0.050	163
Fargo-Moorhead, ND-MN MSA	200,102	4	-0.219	-0.378	-0.513	-0.188	-0.340	-2.158	-1.281	-0.164	0.307	-0.135	-0.068	164
Tulsa, OK MSA	873,304	7	-0.539	-0.527	-0.516	-0.129	-0.069	-1.737	-1.117	-0.219	0.170	-0.127	-0.152	165
Kalamazoo-Battle Creek, MI MSA*	462,250	3	-1.163	-1.175	-0.517	-0.124	-0.110	-0.993	-0.941	-0.062	0.106	-0.131	0.037	166
Omaha, NE-IA MSA	799,130	4	-0.595	-0.618	-0.520	-0.126	-0.065	-0.492	-1.262	-0.092	0.243	-0.126	-0.034	167
Jackson, MS MSA	483,852	6	-0.916	-0.940	-0.523	-0.091	-0.138	-2.341	-0.869	-0.152	0.110	-0.090	-0.110	168
Canton-Massillon, OH MSA*	408,005	3	-0.689	-0.735	-0.524	-0.122	0.048	-1.172	-0.808	-0.066	0.237	-0.142	-0.152	169
Montgomery, AL MSA	354,108	6	-1.023	-1.086	-0.526	-0.136	-0.138	-1.759	-0.897	-0.204	0.047	-0.136	-0.022	170
Memphis, TN-AR-MS MSA	1,230,253	6	-0.737	-0.726	-0.527	-0.050	-0.075	1.490	-0.827	-0.137	0.177	-0.056	0.114	171
Davenport-Moline-Rock Island, IA-IL MSA*	362,790	4	-0.966	-1.018	-0.532	-0.111	0.184	-1.893	-1.201	-0.051	0.179	-0.158	-0.111	172
Houston, TX PMSA	5,219,317	7	-0.359	-0.336	-0.537	0.014	0.036	-0.124	-1.013	-0.121	0.314	-0.001	-0.070	173
Rochester, NY MSA*	1,093,434	2	-1.883	-1.896	-0.538	-0.089	-0.071	-0.614	0.071	0.007	0.038	-0.122	-0.009	174
Toledo, OH MSA*	631,275	3	-1.317	-1.322	-0.540	-0.096	-0.217	-2.296	-0.494	-0.010	0.135	-0.093	-0.202	175
Tyler, TX MSA	204,665	7	-0.962	-1.057	-0.541	-0.146	-0.862	-0.116	-0.930	-0.204	0.077	-0.036	0.114	176
Pittsburgh, PA MSA*	2,287,106	2	-0.866	-0.844	-0.542	-0.097	-0.118	-0.131	0.050	0.016	0.268	-0.098	-0.072	177
Rockford, IL MSA	409,058	3	-0.622	-0.564	-0.542	-0.089	-0.011	-1.104	-1.319	0.103	0.395	-0.100	-0.188	178
Brazoria, TX PMSA	309,208	7	-0.730	-0.730	-0.542	0.035	0.056	-0.871	-1.013	-0.121	0.205	0.007	-0.138	179
Johnson City-Kingsport-Bristol, TN-VA MSA	503,010	6	-0.590	-0.634	-0.550	-0.217	-0.206	-1.569	1.292	-0.221	0.184	-0.192	-0.018	180
Oklahoma City, OK MSA	1,213,704	7	-0.887	-0.905	-0.550	-0.154	-0.276	-1.133	-1.305	-0.175	0.134	-0.129	-0.084	181
Sioux Falls, SD MSA	224,266	4	-0.045	-0.146	-0.554	-0.182	0.181	-1.485	-1.260	-0.189	0.395	-0.203	0.029	182
Amarillo, TX MSA	238,299	7	-0.677	-0.749	-0.554	-0.176	-0.414	-0.910	-1.254	-0.181	0.189	-0.124	-0.110	183
Springfield, MO MSA	383,637	4	-0.618	-0.643	-0.559	-0.201	-0.260	-1.394	-1.100	-0.098	0.271	-0.169	-0.031	184

TABLE A2: LIST OF METROPOLITAN INDICES RANKED BY HOUSING PRICE DIFFERENTIAL, 2005-2010

			Adjusted Differentials					*Raw Differentials*			*Productivity*			
Full Name	Population	Census Division	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	Tradea-bles	Regulatory Cost Index	Housing Price Rank
Fort Worth-Arlington, TX PMSA	2,113,278	7	-0.575	-0.572	-0.568	-0.014	0.000	-0.478	-1.185	-0.172	0.242	-0.028	-0.098	185
Lafayette, IN MSA	202,331	3	-0.281	-0.297	-0.569	-0.207	-0.454	-1.015	-0.147	-0.090	0.392	-0.138	0.061	186
Lafayette, LA MSA	415,592	7	-1.074	-1.169	-0.571	-0.118	-0.065	-1.803	-1.327	-0.190	0.087	-0.130	-0.150	187
Utica-Rome, NY MSA*	293,280	2	-1.809	-1.889	-0.575	-0.082	-0.267	-1.495	-0.556	-0.048	0.041	-0.084	-0.046	188
Fayetteville, NC MSA	315,207	5	-0.952	-1.000	-0.575	-0.191	-0.259	-1.631	-0.663	-0.229	0.097	-0.169	-0.205	189
San Antonio, TX MSA	1,928,154	7	-0.801	-0.800	-0.590	-0.126	-0.136	1.707	-1.270	-0.187	0.185	-0.120	0.071	190
Buffalo-Niagara Falls, NY MSA*	1,123,804	2	-1.056	-1.054	-0.593	-0.076	-0.067	-1.215	-0.490	0.034	0.281	-0.090	-0.080	191
Syracuse, NY MSA*	725,610	2	-1.452	-1.456	-0.595	-0.091	-0.040	-1.782	-0.549	-0.016	0.158	-0.117	-0.168	192
Lake Charles, LA MSA	187,554	7	-0.822	-0.925	-0.605	-0.079	0.268	-2.005	0.980	-0.190	0.190	-0.136	-0.224	193
Macon, GA MSA	356,873	5	-0.963	-0.989	-0.606	-0.076	-0.097	-1.734	-1.038	-0.172	0.164	-0.083	-0.134	194
Erie, PA MSA*	280,291	2	-1.297	-1.354	-0.611	-0.163	-0.211	-0.980	1.080	-0.042	0.185	-0.158	-0.047	195
St. Joseph, MO MSA*	106,908	4	-1.155	-1.251	-0.619	-0.112	0.000	-2.497	-1.119	-0.050	0.219	-0.029	-0.085	196
Longview-Marshall, TX MSA	222,489	7	-1.202	-1.245	-0.619	-0.123	-0.377	-2.513	-0.903	-0.290	0.028	-0.092	-0.181	197
Elkhart-Goshen, IN MSA	200,502	3	-0.995	-1.028	-0.622	-0.097	-0.071	-1.531	-1.100	-0.001		-0.108		198
Lubbock, TX MSA	270,550	7	-1.027	-1.039	-0.628	-0.185	-0.207	-1.611	-1.404	-0.209	0.143	-0.172	-0.026	199
Saginaw-Bay City-Midland, MI MSA*	390,032	3	-1.736	-1.763	-0.629	-0.118	-0.165	-0.236	-0.620	-0.035	0.122	-0.132	-0.042	200
Evansville-Henderson, IN-KY MSA	305,455	3	-1.531	-1.667	-0.632	-0.136	-0.347	-1.385	-1.000	-0.070	0.136	-0.117	-0.053	201
Corpus Christi, TX MSA	391,269	7	-1.010	-1.047	-0.633	-0.154	-0.155	-1.222	0.443	-0.230	0.137	-0.150	-0.190	202
South Bend, IN MSA*	267,613	3	-0.305	-0.410	-0.639	-0.182	0.057	-2.105	-0.907	-0.080	0.460	-0.191	-0.050	203
Wichita, KS MSA	589,195	4	-0.820	-0.889	-0.641	-0.112	-0.183	-1.987	-1.345	-0.176	0.237	-0.101	-0.063	204
Rocky Mount, NC MSA	146,596	5	-0.236	-0.382	-0.641	-0.100	-0.275	-0.921	-0.519	-0.314	0.333	-0.061	-0.146	205
Fort Smith, AR-OK MSA	225,132	7	-1.336	-1.409	-0.650	-0.222	-0.200	-1.839	-0.454	-0.205	0.089	-0.217	-0.166	206
El Paso, TX MSA	751,296	7	-0.662	-0.699	-0.657	-0.215	-0.182	0.350	-1.174	-0.234	0.260	-0.195	-0.030	207
Flint, MI PMSA*	424,043	3	-1.179	-1.152	-0.681	-0.010	-0.037	-0.528	-0.955	-0.010	0.306	-0.034	0.060	208
Fort Wayne, IN MSA	528,408	3	-0.866	-0.871	-0.685	-0.142	-0.142	-1.612	-1.300	-0.105	0.320	-0.137	-0.079	209
Killeen-Temple, TX MSA	358,316	7	-1.153	-1.187	-0.691	-0.180	-0.219	-1.913	-1.262	-0.260	0.135	-0.169	-0.051	210
Binghamton, NY MSA*	244,694	2	-1.494	-1.571	-0.699	-0.104	0.088	-1.494	0.262	-0.035	0.235	-0.151	-0.109	211
Sherman-Denison, TX MSA	120,030	7	-1.410	-1.390	-0.728	-0.160	-0.024	-1.719	-1.090	-0.001		-0.112		212
Beaumont-Port Arthur, TX MSA*	378,477	7	-1.140	-1.167	-0.731	-0.051	-0.259	-1.492	-0.499	-0.176	0.241	-0.039	-0.094	213
Youngstown-Warren, OH MSA*	554,614	3	-1.507	-1.526	-0.739	-0.169	-0.232	-0.842	-0.909	-0.039	0.271	-0.166	-0.155	214
Bismarck, ND MSA	106,286	4	-0.672	-0.797	-0.768	-0.218	-0.262	-0.505	-1.138	-0.169	0.413	-0.187	-0.069	215
Sioux City, IA-NE MSA*	123,482	4	-1.670	-1.770	-0.822	-0.227	-0.590	-1.938	-1.276	-0.149	0.231	-0.172	-0.102	216
Brownsville-Harlingen-San Benito, TX MSA	396,371	7	-0.920	-0.954	-0.955	-0.239	-0.280	-0.811	-0.068	-0.001		-0.210		217
McAllen-Edinburg-Mission, TX MSA	741,152	7	-0.398	-0.409	-0.957	-0.205	-0.136	-0.795	-1.380	-0.261	0.627	-0.186	-0.109	218
<u>*Census Divisions:*</u>														
New England	8,966,068	1	0.050	0.010	0.423	0.092	0.117	0.912	0.240	0.126	-0.332	0.072	0.186	5
Middle Atlantic	36,338,768	2	0.323	0.278	0.262	0.072	0.121	0.144	0.080	0.165	-0.013	0.059	-0.014	2
East North Central	34,462,007	3	-0.407	-0.405	-0.272	-0.036	-0.047	-0.689	-0.299	0.030	0.146	-0.038	-0.064	6
West North Central	12,363,802	4	-0.495	-0.513	-0.339	-0.063	-0.085	-1.002	-0.900	0.017	0.173	-0.059	-0.054	7
South Atlantic	41,912,174	5	0.105	0.109	-0.050	-0.031	-0.032	0.015	0.177	-0.102	0.017	-0.023	0.000	4
East South Central	9,366,975	6	-0.629	-0.642	-0.419	-0.105	-0.138	-0.934	-0.418	-0.141	0.103	-0.096	-0.026	9
West South Central	26,109,488	7	-0.567	-0.569	-0.521	-0.066	-0.080	-0.526	-0.795	-0.164	0.198	-0.066	-0.084	8
Mountain	15,672,803	8	0.148	0.157	-0.056	-0.040	-0.084	0.296	-0.046	-0.096	0.034	-0.022	0.035	3
Pacific	40,847,165	9	0.677	0.643	0.606	0.080	0.089	0.668	0.988	0.089	-0.306	0.080	0.087	1
<u>*Metropolitan Population:*</u>														
Less than 500,000	31,264,023		-0.525	-0.563	-0.225	-0.065	-0.077	-0.438	-0.041	-0.055	0.000	-0.063	-0.016	4
500,000 to 1,500,000	55,777,644		-0.411	-0.423	-0.202	-0.053	-0.066	-0.345	-0.159	-0.060	0.021	-0.052	-0.023	3
1,500,000 to 5,000,000	89,173,333		0.163	0.159	0.074	0.013	0.009	0.131	0.174	0.005	-0.016	0.015	0.016	2
5,000,000+	49,824,250		0.613	0.589	0.316	0.078	0.113	0.173	0.012	0.103	-0.022	0.073	0.005	1

Figure A: Construction Wages vs. Overall Wages

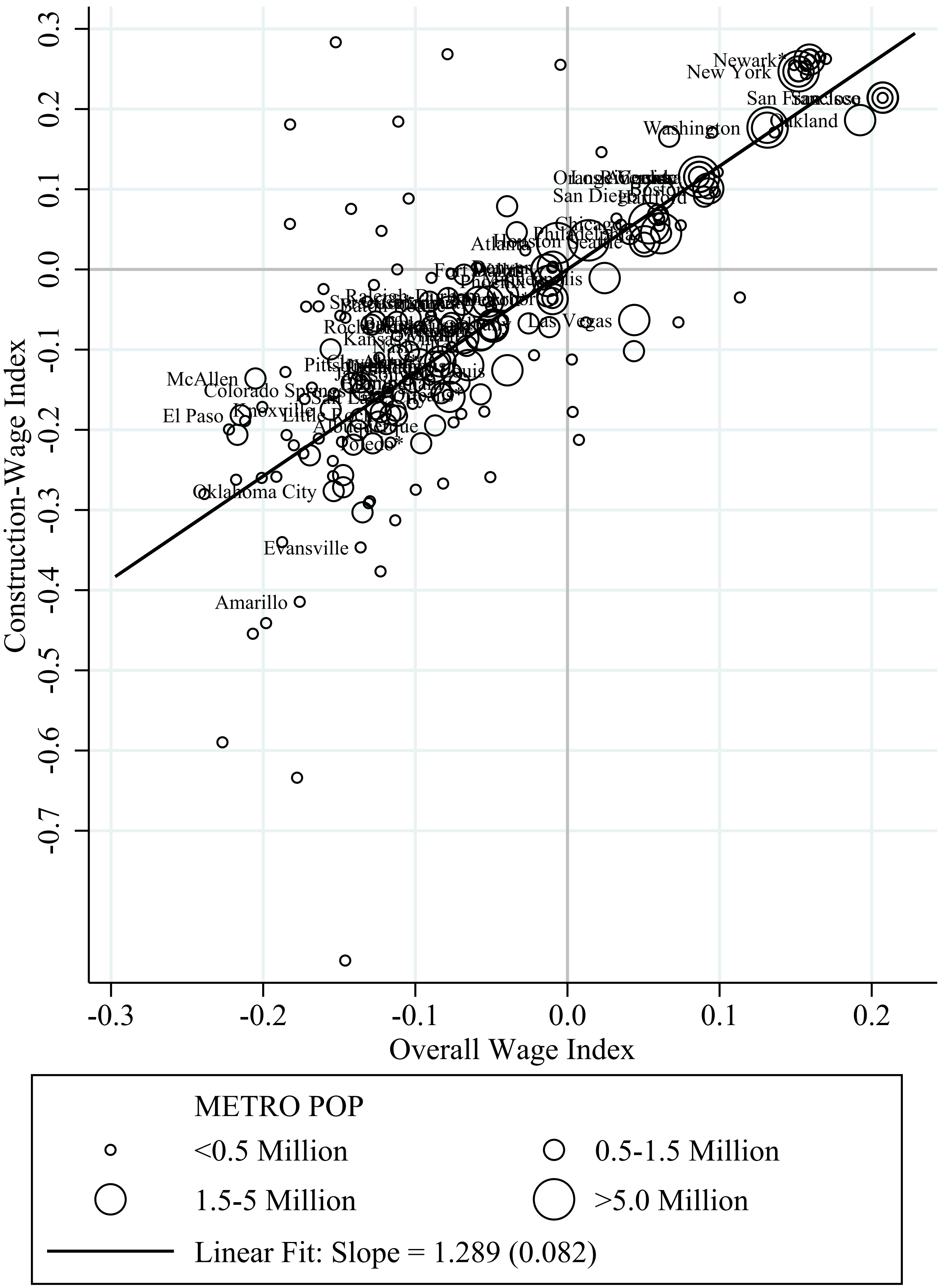


Figure B: Construction Prices vs. Construction Wages