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METROPOLITAN LAND VALUES AND HOUSING PRODUCTIVITY

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ABSTRACT

We present the first nationwide index of directly-measured land values by metropolitan area and investigate their relationship with housing prices. Construction prices and geographic and regulatory constraints are shown to increase the cost of housing relative to land. On average, approximately one-third of housing costs are due to land, with an increasing share in higher-value areas, implying an elasticity of substitution between land and other inputs of about one-half. Conditional on land and construction prices, housing productivity is relatively low in larger cities. The increase in housing costs associated with greater regulation appears to outweigh any benefits from improved quality-of-life.

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1 Introduction

Households spend more on housing than any other good, and the value of housing depends fundamentally on the land upon which it is built. Land values can vary tremendously, reflecting the scarcity of the many heterogeneous amenities and labor-market opportunities to which land provides access. They also reflect opportunities for development, as land that cannot be built on generally has little private value. Land values are quite possibly the most fundamental prices examined in spatial and urban economics.

Accurate data on land values have been notoriously piecemeal, although data on housing values are widespread. Housing values can differ considerably from land values, partly because of the labor and material costs of producing housing structures. The topographical nature of a land parcel's terrain can also influence the quantities of inputs needed to produce housing structures. Restrictions and regulations on land use can raise expensive barriers to building, which can lower the efficiency with which housing services are provided to occupants, creating what is often referred to as a "regulatory tax." While these regulations may be costly, they could also provide benefits to local residents by promoting positive neighborhood externalities, or curtailing negative ones. Whether land-use regulations are welfare improving is perhaps the most hotly debated issue in the microeconomics of housing.

Here, we provide the first inter-metropolitan index of directly-observed land values that covers a large number of American metropolitan areas, using recent data from CoStar, a commercial real estate company. This index varies far more than a similarly constructed index of housing values; the two indices are strongly but imperfectly correlated, with potentially informative deviations. We use duality methods (Fuss and McFadden 1978) to estimate the cost relationship between housing output and input prices using these land and housing-value indices, together with indices on non-land input prices and other measures. This supply-side approach to valuing housing strongly complements the demand-side approach to studying housing prices, based on housing's proximity to local amenities and labor-market opportunities.

Our analysis provides a new measure of local productivity in the housing sector, which we infer from the difference between the observed price of housing and the cost predicted by land and other input prices. This productivity metric is a summary indicator of how efficiently housing inputs are transformed into valuable housing services within a metropolitan area. It is also a novel indicator of local productivity in sectors that produce goods not traded across cities. This measure may be contrasted with measures of productivity in tradeables sectors, such as in Beeson and Eberts (1989) and Albouy (2009). Using recent measures by Gyourko, Saiz, and Summers (2008) and Saiz (2010), we investigate how local housing productivity is influenced by natural and artificial constraints to development arising from geography and regulation.

We find that, on average, approximately one-third of housing costs are due to land: this share ranges from 11 to 48 percent in low to high-value areas, implying an elasticity of substitution between land and other inputs of about 0.5 in our baseline specification. Consistent estimation of these parameters requires controlling for regulatory and geographic constraints: a standard deviation increase in aggregate measures of these constraints is associated with 8 to 9 percent higher housing costs. We also examine disaggregated measures of regulation and geography and find that approval delays, supply restrictions, local political pressure, and state court involvement predict the lowest productivity levels, although our estimates are imprecise.

Overall, housing productivity differences across metro areas are large, with a standard deviation equal to 23 percent of total costs, with 22 percent of the variance explained by observed regulations. Contrary to assumptions in the literature (e.g. Shapiro 2006 and Rappaport 2007) that productivity in tradeables and housing are the same, we find the two are negatively correlated. For example, the San Francisco Bay Area is extremely efficient in tradable industries, and extremely inefficient in producing housing, largely because of its regulations and geography. In general, we find housing productivity to be decreasing, rather than increasing, in city size, suggesting that there are urban diseconomies of scale in housing production. Additionally, we find that lower housing productivity associated with land-use regulation is correlated with a higher quality of life, suggesting that households may value the neighborhood effects these regulations promote. However, the welfare costs of lower housing productivity appear to outweigh these benefits.

Our transaction-based measure differs from common measures of land values based on the difference between a property's entire value and the estimated value of its structure only. Davis and Palumbo (2007) employ this "residual" method successfully across metro areas, although as the authors note, "using several formulas, different sources of data, and a few assumptions about unobserved quantities, none of which is likely to be exactly right." Moreover, the residual method attributes higher costs due to inefficiencies in factor usage – possibly from geographic and regulatory constraints – to higher land values. This may explain why Davis and Palumbo often find higher costs shares of land than we do.[1]

A number of studies have examined data on both housing and land values. Rose (1992) acquires data across 27 cities in Japan and finds greater geographic land availability is associated with lower land and housing values. Ihlanfeldt (2007) takes measures of assessed land values from tax rolls in 25 Florida counties, and finds that land-use regulations are associated with higher housing prices but lower land values. Glaeser and Gyourko (2003) use an augmented residual method to compare housing and inferred land values across the United States, and find that the two differ most in heavily regulated environments. Glaeser, Gyourko, and Saks (2005b) find that the price of units in Manhattan multi-story buildings exceeds the marginal cost of producing them, attributing the difference to regulation. They find the cost of this regulatory tax is larger than the externality benefits they consider, mainly from preserving views.[2]

The econometric approach we use differs in that it explicitly incorporates a cost function, which models land as a variable input to housing production. This approach has similarities to Epple, Gordon, and Sieg (2010), who use separately assessed land and structure values for houses in Alleghany County, PA, and find land's cost share to be 14 percent. We focus on variation across, rather than within cities, which allows us to identify the cost structure from variation in construction prices, geography, and a wide array of regulations. Unlike Epple et al. and Thorsnes (1997),

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

[2] Other works of note that consider the relationship between land-use regulations, land values, and housing values include Ohls et al. (1974), Courant (1976), and Katz and Rosen (1987).

who uses data from Portland, our estimated elasticity of substitution between land and non-land inputs is less than one, which is consistent with much of the older literature – see McDonald (1981) for a survey – based on within-city variation in housing values.

Three recent papers also make use of the CoStar COMPS data to construct land-value indices. Haughwout, Orr, and Bedoll (2008) construct a land price index for the period 1999-2006 within the New York metro area, documenting many sales within the densest areas of Manhattan, as well as in outlying areas. Kok, Monkkonen, and Quigley (2010) also document land sales throughout the San Francisco Bay Area, and relate the sales prices to the topographical, demographic, and regulatory features of the site. Nichols, Oliner, and Mulhall (2010) construct a panel of land-value indices for 23 metro areas from the 1990s through 2009. They demonstrate that land values vary more across time than housing values, much as our analysis demonstrates is true across space.

Section 2 presents our cost-function approach for modeling housing prices and relates it to an econometric model. It also provides a general-equilibrium model for the full determination of land values. Section 3 discusses our data and explains how we use them to construct indices of land values, housing prices, construction prices, geography, and regulation across metro areas. Section 4 presents our estimates of the housing-cost function and how housing productivity is influenced by geographic and regulatory constraints. Section 5 considers how housing productivity varies across cities and is related to measures of urban productivity in tradeables and quality of life.

2 Model of Land Values and Housing Production

Our econometric model uses a cost function for housing production within a system-of-cities model, proposed by Roback (1982), and developed by Albouy (2009). 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_Y^j.

2.1 Cost Function for Housing

We begin with a two-factor model in which firms produce housing, Y_j, using land L and materials M according to the production function

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

where F_j^Y is concave and exhibits constant returns to scale (CRS) in L and M at the firm level. Housing productivity, A_j^Y, is a city-level characteristic that may be fixed or determined endogenously by city characteristics, such as population size. Land is paid a city-specific price, r_j, while materials are paid price v_j. In our empirical work, we operationalize M as the installed structure component of housing, so v_j is conceptualized as an index of construction input prices, possibly an aggregate of local labor and mobile capital. Unit costs in the housing sector, equal to marginal and average costs, are $c^Y(r_j, v_j; A_j^Y) \equiv \min_{L,M}\{r_jL + v_jM : F_Y(L, M; A_j^Y) = 1\}$.

The use of a single function to model the production of a heterogenous housing stock is well established in the literature, beginning with Muth (1960) and Olsen (1969). In the words of Epple et al. (2010, p. 906)

> The production function for housing entails a powerful abstraction. Houses are viewed as differing only in the quantity of services they provide, with housing services being homogeneous and divisible. Thus, a grand house and a modest house differ only in the number of homogeneous service units they contain.

This abstraction also implies that a highly capital-intensive form of housing, e.g., an apartment building, can substitute in consumption for a highly land-intensive form of housing, e.g., single-story detached houses.[3]

Assuming the housing market in city j is perfectly competitive[4], then in equilibrium housing

[3] Our analysis uses data from owner-occupied properties, accountiing for 67% of homes, of which 82% are single-family and detached.

[4] Although this assumption may seem stringent, the empirical evidence is consistent with perfect competition in the construction sector. Considering evidence from the 1997 Economic Census, Glaeser et al. (2005b) report that

price equals the unit cost in cities with positive production:

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

Our methodology of estimating housing productivity is illustrated in figure 1A, holding v_j constant. The thick solid curve represents the cost function of housing 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 input. The higher, thinner curve represents the cost function for a city with lower productivity, such as San Francisco. The lower productivity level is identified by how much higher the housing price in San Francisco is relative to a city with the same factor costs, such as in New York.

The first-order log-linear approximation of equation (2) around the national average expresses how housing prices should vary with input prices and productivity, $\hat{p}_j = \phi^L \hat{r}_j + (1-\phi^L)\hat{v}_j - \hat{A}_j^Y$. $\hat{z}^j$ represents, for any z, city j's log deviation from the national average, $\bar{z}$, i.e. $\hat{z}^j = \ln z^j - \ln \bar{z}$. ϕ^L is the cost share of land in housing at the average, and A_Y^j is normalized so that a one-point increase in $\hat{A}_j^Y$ corresponds to a one-point reduction in log costs.[5] Rearranged, this equation infers home-productivity from how high land and material costs are relative to housing costs:

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

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

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

"...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.

[5]This requires that productivity at the national average obeys $\bar{A}^Y = -\bar{p}/[\partial c^Y(\bar{r}, \bar{m}, \bar{A}^Y)/\partial A]$.

where σ^Y is the elasticity of substitution between land and non-land inputs. This 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 actual cost share is not constant across cities, but is approximated by

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

and thus is increasing with $\hat{r}_j - \hat{v}_j$ when $\sigma^Y < 1$. Our estimates of $\hat{A}_j^Y$ assume that a single elasticity of substitution describes production in all cities. If this elasticity varies, then our estimates will conflate a lower elasticity with lower productivity. This is seen in figures 1A and 1B, which compares $\sigma^Y = 1$ in the solid curves, with $\sigma^Y = 1$ in the dashed curves. When production has low substitutability, the cost curve is flatter, as housing does not use less land in higher-value cities. This has the same observable consequence of increasing housing prices, although theoretically the concepts are different.[6]

If housing productivity is not factor neutral, then as derived in Appendix A, equation (4) contains additional terms to account for the productivity of land relative to materials, A_j^{YL}/A_j^{YM}:

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

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

2.2 Econometric Model

As a starting point, we estimate housing prices using an unrestricted translog cost function (Christensen et al. 1973) in terms of land and non-land factor prices:

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

[6]Housing supply, as a quantity, is less responsive to price increases when substitutability is low, rather than when productivity is low. While it would be desirable to distinguish the two, this would be significantly more challenging and require much additional data, and so we leave it for future work.

where Z^j is a vector of city-level observable attributes that may affect housing prices. This specification is equivalent to the second-order approximation of the cost function (see, e.g., Binswager 1974, Fuss and McFadden 1978) under the restrictions imposed by CRS

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

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 is determined by attributes in Z^j and unobservable attributes in the residual, ε_j:

$$\hat{A}^j_Y = Z^j(-\gamma) + \hat{A}^j_{0Y},\ \hat{A}^j_{0Y} = -\varepsilon_j. \tag{9}$$

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). The assumption of Cobb-Douglas (CD) production technology imposes the restriction $\sigma^Y = 1$, which in equation (7) amounts to the three restrictions:

$$\beta_3 = \beta_4 = \beta_5 = 0. \tag{10}$$

Without additional data, non-neutral productivity differences are impossible to detect unless we know what may shift A^{YL}_j/A^{YM}_j. In the context, 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 may be written as:

$$\hat{p}_j - \hat{v}_j = \beta_1(\hat{r}_j - \hat{v}_j) + \beta_3\left[(\hat{r}_j)^2 + (\hat{v}_j)^2 - 2(\hat{r}_j\hat{v}_j)\right] + \gamma_1 Z^j + \gamma_2 Z^j\left(\hat{r}_j - \hat{v}_j\right) + \varepsilon_j \tag{11}$$

As shown in Appendix A, $\gamma_2 Z^j/2\beta_3 = (\hat{A}^{YM}_j - \hat{A}^{YL}_j) - (\hat{A}^{YM}_{0j} - \hat{A}^{YL}_{0j})$ 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.[7]

[7] In equation (11), non-neutral productivity implies $\beta_1 = \phi_L + \beta_3(\hat{A}^{YM}_{0j} - \hat{A}^{YL}_{0j})$ and $\varepsilon^j = -[\phi^L \hat{A}^{YL}_j + (1 -$

2.3 Full Determination of Land Values

In this section, we determine land values and local-wage levels in a model of location demand based on amenities to households, bundled as quality of life, Q_j, and to firms in the tradeable sector, bundled as trade productivity, A_j^X. Casual readers may skip this section without loss of intuition. We posit two types of mobile workers, $k = X, Y$, where type-Y workers work in the housing sector. Preferences are modeled by the utility function $U^k(x, y; Q_j^k)$, which is quasi-concave over consumption x and y, and increases in Q_j^k, which may vary by type. The household expenditure function is $e^k(p, u; Q) \equiv \min_{x,y}\{x + py : U^k(x, y; Q) \geq u\}$. Each household supplies a single unit of labor and is paid $w_{j,}^k$, 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. We assume households are mobile and that both types occupy each city. Equilibrium requires that households receive the same utility in all cities, so that higher prices or lower quality-of-life must be compensated with greater after-tax income, $e^k(p_j, \bar{u}^k; Q_j^k) = m_j^k - \tau(m_j^k)$, $k = X, Y$, where $\bar{u}^k$ is the level of utility attained nationally by type k. Log-linearizing this condition around the national average

$$\hat{Q}_j^k = s_y^k \hat{p}_j - (1 - \tau^k) s_w^k \hat{w}_j^k, \ k = X, Y. \tag{12}$$

Q_j^k is normalized $\hat{Q}_j^k$ is equivalent to a one-percent drop in total consumption, s_y^k is the average expenditure share on housing, and τ^k is the average marginal tax rate, and s_w^k is the share of income from labor. Define the aggregate quality-of-life differential $\hat{Q}_j \equiv \mu^X \hat{Q}_j^X + \mu^Y \hat{Q}_j^Y$, where μ^k is the share of income earned by type k households, and let $s_y \equiv \mu^X s_y^X + \mu^Y s_y^Y$, and $(1 - \tau) s_w \hat{w} \equiv \mu^X (1 - \tau^X) s_w^X \hat{w}_j^X + \mu^Y (1 - \tau^Y) s_w^Y \hat{w}_j^Y$.

Unlike housing output, tradeable output has a uniform price across all cities, and is produced through the CRS and CD function, $X_j = F^X(L^X, N^X, K^X; A_j^X)$, where N^X is labor and K^X is mobile capital, which also has the uniform price, i, everywhere. We also assume that land commands the same price, r_j, within a city in all sectors. A derivation similar to the one for (3)

$\phi^L)\hat{A}_j^{YM}] + (1/2)\phi^L(1 - \phi^L)(1 - \sigma^Y)(\hat{A}_j^{YL} - \hat{A}_j^{YM})^2$

yields the measure of tradeable productivity:

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

where $\theta^L$and θ^N are the average cost-shares of land and labor in the tradeable sector.

To complete the model, let non-land inputs be produced through the CRS and CD function $M_j = (N^Y)^a (K^Y)^{1-a}$, 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:

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

Combining the productivity in both sectors, the total-productivity differential of a city is

$$\hat{A}_j \equiv s_x \hat{A}_j^X + s_y \hat{A}_j^Y, \tag{15}$$

where s_x is the average expenditure share on tradeables.

Combining the first-order approximation equations (12), (13), (14), and (15), we get that the land-value differential times the average income share of land, $s_R = s_x\theta_L + s_y\phi_L$, equals the total productivity differential plus the quality-of-life differential, minus the tax differential to the federal government, $\tau s_w \hat{w}_j$:

$$s_R \hat{r}_j = s_x \hat{A}_j^X + s_y \hat{A}_j^Y + \hat{Q}_j - \tau s_w \hat{w}_j. \tag{16}$$

In other words, land fully capitalizes the value of local amenities minus federal tax payments.

Proper identification of the model requires that the observed determinants of land values, $\hat{r}_j$, $\hat{w}_j$, and Z_j are uncorrelated with unobserved determinants of A_j^Y in the residual, ε_j. To some extent, this is inevitable if the vector of characteristics Z_j is incomplete and $\hat{A}_j^{Y0} = -\varepsilon_j \neq 0,$ as $\hat{r}_j$ is determined by $\hat{A}_j^Y$ in (16). We have considered modeling the simultaneous determination of $\hat{r}_j$ by $\hat{A}_j^{Y0}$, but this requires knowing the covariance structure between $\hat{A}_j^X$,$\hat{A}_j^Y$, and $\hat{Q}_j$. A more promising approach is to find instrumental variables (IVs) that influence $\hat{A}_j^X$ or $\hat{Q}^j$ but are unrelated to $\hat{A}_j^Y$. Below, we consider two instruments for land and non-land input prices that we think are plausible, although certainly not unassailable. The first is the inverse distance to the nearest salt-water coast. The second is average winter temperature. We find the IV estimates are consistent with, but less precise than, our ordinary least square (OLS) results, and thus focus on the latter. The geographic constraints are predetermined, so we treat them as exogenous. We have not found a plausible strong instrument for regulatory constraints.

3 Data and Metropolitan Indicators

3.1 Land Values

We calculate our land-value index from transactions prices reported in the CoStar COMPS database. The CoStar Group provides commercial real estate information and claims to have the industry's largest research organization, with researchers making over 10,000 calls a day to commercial real estate professionals. The COMPS database includes transaction details for all types of commercial real estate, including what they term "land." In this study, we take every land sale in the COMPS database provided by CoStar University, which is provided for free to academic researchers.

Our sample includes transactions that occurred between 2005 and 2010 in a Metropolitan Statistical Area (MSA).[8] It excludes all transactions CoStar has marked as non-arms length or without complete information for lot size, sales price, county, and date, or that appear to feature a structure. Finally, we drop observations we could not geocode successfully, leaving us with 68,757 observed land sales.[9]

CoStar provides a field describing the "proposed use" of each property, useful for our analysis.

[8] We use the June 30, 1999 definitions provided by the Office of Management and Budget. The data are organized by Primary Metropolitan Statistical Areas (PMSAs) within larger Consolidated Metropolitan Statistical Areas (CMSAs).

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

We use 12 of the most common categories of "proposed use," which are neither mutually exclusive nor collectively exhaustive. Properties can have multiple proposed uses or none at all. Thus, we also use an indicator for no proposed use.

The median price per acre in our sample is $272,838, while the mean is $1,536,374; the median lot size is 3.5 acres while the mean is 26.4. Land sales occur more frequently in the beginning of our sample period, with 21.7% of our sample from 2005, and 11.4% from 2010. The frequencies of proposed uses are reported in table 1: 17.6% is for residential, including 10.7% is for single-family homes, 3.3% for multi-family; and 3.6% for apartments; industrial, office, retail, medical, parking, and commercial uses together account for 24.1%. 23.4% is being held for development or investment, and 15.9% of the sample had no proposed use.

We calculate the metropolitan index of land values by regressing the log price per acre of each sale, $\ln \tilde{r}_{ijt}$ on a set of a vector of controls, X_{ijt}, and a set of indicator variables for each year-MSA interaction, ψ_{jt} in the equation $\ln \tilde{r}_{ijt} = X_{ijt}\beta + \psi_{jt} + e_{ijt}$. In our regression tables we use land-value indices, $\hat{r}_{jt}$, based on estimates of ψ_{jt} by year and MSA, normalized to have a national average of zero, weighting by number of housing units; in our summary statistics and figures, we report land-value indices, $\hat{r}_j$, aggregated across years. Furthermore, because of our limited sample size, land-value indices derived from metro areas with fewer land sales may exhibit excess dispersion because of sampling error. We correct for this using shrinkage methods described in Kane and Staiger (2008), accounting for yearly as well as metropolitan variation in the estimated $\hat{\psi}_{jt}$. The shrinkage effects are generally small, but do appear to correct for mild amounts of attenuation bias in our subsequent analysis.

Table 1 reports the results for four successive land-value regressions. The first regression has no controls. In column 2, we control for log lot size in acres, which improves the R^2 substantially from 0.30 to 0.70. The coefficient on lot size is -0.66, illustrating the "plattage effect," documented by Colwell and Sirmans (1980, 1993). According to these authors, when there are costs to subdividing parcels (e.g. because of zoning restrictions), large lots contain more land than is optimal for their intended use, thus lowering their value per acre. Another possible explanation for this effect is that large lots are located in less desirable areas. In column 3, we add controls for intended use raising the R^2 to 0.71. These intended uses help control for various characteristics of the land parcels, although ultimately their inclusion has little impact on our land-value index.

The sample of land parcels in our data set is not a random sample of all lots, which raises the concern of sample selection bias. As discussed in Nichols et al. (2010), it is impossible to correct for this selection bias because we do not observe prices for unsold lots.[10] One especially relevant source of selection bias is that the geographic distribution of sales may differ systematically from the overall distribution of land. For instance, we may be more likely to observe land sales on the urban fringe, where development activity is more intense. Such land will more closely reflect agricultural land values, thus attenuating land-value differences across cities.

To handle sample selection, we re-weight our land observations to reflect the distribution of housing units in the metro area. For each MSA, we pinpoint the metropolitan center using Google Maps.[11] Then, we regress the log number of housing units per square mile at the census-tract level on the North-South and East-West distances between the tract center and the city center, and the squares and product of these distances. We calculate the predicted density of each observed land sale using the city-specific coefficients from this regression, and use this predicted density in column 4, which we take as our preferred specification. The un-weighted and weighted indices are highly correlated (the correlation coefficient is above 0.99), although the latter are more dispersed, as predicted.

Because our focus is on residential housing, we were initially concerned about using land sales with non-residential proposed uses. Ultimately, we find that indices constructed only from land sales with a proposed residential use do not differ systematically from our preferred index, except that they are less precise. Nonetheless, when we conduct our analysis below using residential-only indices, our chief results are largely unaffected, although we lose some MSAs from our sample.

Our preferred land-value index is based on the shrunken and weighted estimators based on

[10] There is a modest literature that attempts to control for selection bias in commercial real estate and land prices, for example, Colwell and Munneke (1997), Fisher et al. (2007), and Munneke and Slade (2000, 2001). Sample selection generally appears to be weak in this context.

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

all land sales, as described above. To illustrate the impact of these choices, figure A contrasts the differences between shrunken and unshrunken indices; figure B, between weighted and unweighted indices; and figure C, between using all land and land only for residential uses. While there are some differences between these indices, their overall patterns are rather similar.

Land values for a selected group of metropolitan areas are reported in table 2, together with averages by metropolitan population size. These values are very dispersed, with a weighted standard deviation of 0.76. The highest land values in the sample are around New York City, San Francisco, and Los Angeles; the lowest are in Saginaw, Utica, and Rochester, which has land values 1/35th those of New York City. In general, large, coastal cities have the highest land values, while smaller cities in the South and Midwest have lower values.

3.2 Housing Prices, Wages, and Construction Prices

We calculate housing-price and wage indices for each year from 2005 to 2010 using the 1% samples from the American Community Survey. Our method, described in detail in Appendix B, mimics that for land values. For each year, we regress housing prices of owner-occupied units on a set of indicators for each MSA, controlling flexibly for observed housing characteristics, including age and type of building structure, number of rooms and bedrooms interacted, and kitchen and plumbing facilities. The coefficients on these metro indicators, normalized to have a weighted average of zero, provide our index of housing prices, $\hat{p}_{jt}$, which we aggregate across years for display.

We estimate wage levels in a similar fashion, controlling for worker skills and characteristics. We estimate indices for all workers, $\hat{w}_j$, and for the purpose of our cost estimates, workers in the construction industry only, $\hat{w}_j^Y$. As seen in figure D, $\hat{w}_j^Y$ is similar to, but more dispersed than, overall wages, $\hat{w}_j$.[12]

Our primary price index for construction inputs is calculated from the Building Construction Cost data from the RS Means company, widely used in the literature, e.g., Davis and Palumbo

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

(2007), and Glaeser et al. (2005b). For each city in their 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.[13]

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

The housing-price, construction-wage, and construction-cost indices, reported in columns 2, 3, and 4 of table 2, are strongly related to city size and positively correlated with land values. They also exhibit considerably less dispersion. The highest housing prices are in San Francisco, which are 9 times the lowest housing prices, in McAllen, TX. The highest construction prices are in New York City, 1.9 times the lowest, in Rocky Mount, NC.

[13]The RS Means index is based on 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 2010 edition of the RS Means index.

3.3 Regulatory and Geographic Constraints

Our index of regulatory constraints is provided by the Wharton Residential Land Use Regulatory Index (WRLURI), described in Gyourko, Saiz, and Summers (2008). The index is constructed from 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: 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). The authors construct a single aggregate WRLURI index through factor analysis: we consider both the aggregate index and the subindices in our analysis, each of which we renormalize as $z-$scores, with a mean of zero and standard deviation one, as weighted by the housing units in our sample. Typically, the WRLURI subindices are positively correlated, but not always; for instance, the SCII is negatively correlated with five of the other subindices.

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. While this land is not actually built on, it serves as a proxy for geographic features that may lower housing productivity. 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.

According to the aggregate indices, reported in columns 5 and 6, the most regulated land is in Boulder, CO, and the least regulated is in Glens Falls, NY; the most geographically constrained is in Santa Barbara, CA, and the least is in Lubbock, TX.

4 Cost-Function Estimates

Below, we use the indices from section 3 to test and estimate the cost function presented in section 2, and examine how it is influenced by geography and regulation using both aggregated and disaggregated measures. We restrict our analysis to MSAs with at least 10 land-sale observations, and years with at least 5. For our main estimates, the MSAs must also have available WRLURI, Saiz and construction-price indices, leaving 206 MSAs and 856 MSA-years.

4.1 Estimates and Tests of the Model

Figure 2 plots metropolitan housing prices against land values. The simple regression line, weighted by the number of housing units in our sample, has a slope of 0.59; if there were no other cost or productivity differences across cities, this number would estimate the cost share of land, ϕ_L, assuming CD production. The convex curvature in the quadratic regression yields an imprecise estimate of the elasticity of substitution of 0.18.[14] Of course, this regression is biased, as land values are positively correlated with construction prices and geographic and regulatory constraints. This figure illustrates how housing productivity is inferred by the vertical distance between a marker and the regression line. Accordingly, San Francisco has low housing productivity and Las Vegas has high housing productivity.

To illustrate differences in construction prices, we plot them against land values in figure 3A. We use these data to estimate a cost surface shown in figure 3B without controls. As in figure 2, cities with housing prices above this surface are inferred to have lower housing productivity. Figure 3A plots the level curves for the surface in 3B, which correspond to the zero-profit conditions (ZPCs) for housing producers, seen in equation (4). These curves correspond to fixed sums of housing prices and productivities, $\hat{p}_j + \hat{A}_j^Y$, with curves further to the upper-right corresponding to higher sums. With the log-linearization, the slope of the ZPC is the ratio of land cost shares to non-land cost shares, $-\phi_j^L/(1-\phi_j^L)$. In the CD case, this slope is constant, as illustrated by the

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

solid line; with an elasticity, σ^Y, of less than one, the slope of the ZPC increases with land values, as the land-cost share rises with land prices, as illustrated by the dashed curves.

Columns 1 and 2 of table 3 present cost-function estimates using the aggregate geographic and regulatory indices, assuming CD production, as in (10); column 2 imposes the restriction of CRS in (8), which is barely rejected at the 5% level. The CRS restriction is not rejected in the more flexible translog equation, presented in columns 3 and 4. The restricted regression in column 4 estimates the elasticity of substitution σ^Y to be 0.37. While we cannot reject the CD restriction (10) jointly with the CRS restriction (8), our interpretation of the evidence is that the restricted translog equation in column 4 describes the data best and provides fairly good evidence that σ^Y is less than one.

The OLS estimates in columns 1 through 4 produce stable values of 0.37 for the cost-share of land parameter, ϕ_L. Furthermore, we find that a one standard deviation increase in the geographic and regulatory indices predict a 9- and 8-percent increase in housing costs, respectively. These effects are consistent with our theory of housing productivity and the belief that geographic and regulatory constraints impede the production of housing services.

Columns 5 and 6 present our IV estimates, which use inverse distance to a salt-water coast and average winter temperature as instruments for the differentials $(\hat{r}-\hat{v})$ and $(\hat{r}-\hat{v})^2$. in the restricted equation (11) with $\gamma_2 = 0$. Column 5 imposes the CD restriction, $\beta_3 = 0$ and only uses the coastal instrument. Estimates of the first-stage, presented in table A1, reveal that these instruments are strong, with F-statistics of 64 in column 5, and 15 and 17 in column 6. The IV estimates are largely consistent with our OLS estimates, but less precise. The last row of table 3 reports the Chi-squared test of regressor endogeneity, in the spirit of Hausman (1978): these tests do not reject the null of regressor exogeneity at any standard size. The consistency of the IV estimates requires that distance-to-coast and winter temperature are uncorrelated with housing productivity, conditional on measures of geography and regulation. This assumption may be violated, as it may be difficult to build housing in extreme temperatures. We believe our IVs are much more strongly related to quality of life and trade productivity than to housing productivity, and should produce mostly exogenous variation in land values, as expressed in (16). The similarity of our OLS and IV estimates is reassuring and so we proceed under the assumption that the OLS estimates are consistent.

We test the assumption that the productivity shifters are factor neutral in column 7. This allows γ_2 to be non-zero in equation (11) by interacting the differential $(\hat{r} - \hat{v})$ with the geographic and regulatory indices. This interaction does not produce significant estimates of γ_2 and does not change our other estimates significantly. While this test of factor bias is imperfect, the evidence suggests that factor neutrality is not strongly at odds with the data.

Finally, in column 8, we use an alternative measure of non-land input prices, namely wage levels in the construction industry. The results in column 8 are quite similar to those in column 4. We perform a number of additional robustness checks in table A2. We split the sample into two periods: a ”housing-boom” period, from 2005 to 2007, and a ”housing-bust” period, from 2008 to 2010. We also use alternative land-value indices, one using only residential land, a second not controlling for proposed use or lot size, and another not shrinking the land-value index. The last two robustness checks drop observations in our low-growth areas. The results of these robustness checks, discussed in Appendix C, reveal that the regression parameters are surprisingly stable over these specifications.

4.2 Disaggregating the Regulatory and Geographic Indices

As discussed above, the WRLURI regulatory index aggregates 11 subindices, while the Saiz index aggregates two. The factor loading of each of the WRLURI subindices in the aggregate index is reported in column 1 of table 4, 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 slightly from the factor loads because of differences in samples and weights. Column 3 presents similar estimates for the Saiz subindices. The coefficients on these measures are negative because the subindices indicate land that may be available for development.

The specification in column 4 is identical to the specification in column 4 of table 3, but with the disaggregated regulatory and geographic subindices. The results indicate that approval delays, local political pressure, state political involvement, supply restrictions, and state court involvement are all associated with economically significant reductions in housing productivity, ranging between 3- to 7- percent for a one-standard deviation increase. All five subindices are statistically significant at the 10-percent level, although only the last three are significant at 5 percent: these tests may lack precision because of the high degree of correlation between the subindices. None of the subindices has a significantly negative coefficient. The first three subindices are roughly consistent with the factor loading; the last two, for supply restrictions and state court involvement, appear to be of greater importance than a single-factor model captures.

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

Overall, the results of these regressions are encouraging. The estimated cost share of land and the elasticity of substitution between land and other inputs into housing production in our regressions are quite plausible, and the coefficients on the regulatory and geographic variables have the predicted signs and reasonable magnitudes. The tight fit of the cost-function specification, as measured by the R^2 values approaching 90 percent, implies that even our imperfect measures of input prices and observable constraints explain the variation in housing prices across metro areas quite well.

As our favored specification, we take the one from column 4 of table 4 – with CRS, factor-neutrality, non-unitary σ^Y, and disaggregated subindices – and use it for our subsequent analysis. It provides a value of $\phi_L = 0.33$ and $\sigma^Y = 0.49$. Using formula (5), this implies that the cost share of land ranges from 11 percent in Rochester to 48 percent in New York City.

5 Housing Productivity across Metropolitan Areas

5.1 Productivity in Housing and Tradeables

In column 1 of table 5 we list our inferred measures of housing productivity from the favored specification, using both observed and unobserved components of housing productivity, i.e., $\hat{A}_j^Y = Z_j(-\hat{\gamma}) - \hat{\varepsilon}_j$; column 2 reports only the value of productivity predicted by the regulatory subindices, Z_j^R, i.e., $\hat{A}_j^{YR} = -\hat{\gamma}_1^R Z_j^R$. The cities with the most and least productive housing sectors are McAllen, TX and San Luis Obispo, CA. Among large metros, with over one million inhabitants the top five, excluding our low-growth sample, are Houston, Indianapolis, Kansas City, Fort Worth, and Columbus; the bottom five are San Francisco, San Jose Oakland, Los Angeles, and Orange County, all on California's coast. Along the East Coast, Bergen-Passaic and Boston are notably unproductive. Cities with average productivity include Phoenix, Chicago, and Miami. Somewhat surprisingly, New York City is in this group. Although work by Glaeser et al. (2005b) suggests this is not true of Manhattan, the New York PMSA includes all five boroughs and Westchester county, and houses nearly 10 million people.[15]

In addition, we provide estimates of trade productivity $\hat{A}_j^X$ and quality-of-life $\hat{Q}_j$ in columns 3 and 4, using formulas (13) and (12), calibrated with parameter values taken from Albouy (2009).[16] Housing productivity is plotted against trade productivity in figure 4. This figure draws level curves for total productivity averaged across the housing and tradeables sectors, weighted by their expenditure shares, according to formula (15).[17]

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

[16]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 (2009). 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.

[17]The estimated productivities are positively related to the housing supply elasticities provided by Saiz (2010): a 1-point increase in productivity predicts a 1.94-point (s.e. = 0.24) increase in the supply elasticity ($R^2 = 0.41$).

Our estimates of trade-productivity, based primarily on overall wage levels, are largely consistent with the previous literature.[18] Interestingly, trade productivity and housing productivity are negatively, rather than positively, correlated. According to the regression line, a 1-point increase in trade-productivity predicts a 1.7-point decrease in housing productivity. For instance, cities in the San Francisco Bay Area have among the highest levels of trade productivity and the lowest levels of housing productivity. On the other hand, Houston, Fort Worth, and Atlanta are relatively more productive in housing than in tradeables. The large metro area with the greatest overall productivity is New York; that with the least is Tucson.

The negative relationship between trade and housing productivity estimates may stem from differing scale economies at the city level. While trade productivity is known to increase with city size (e.g., Rosenthal and Strange, 2004), it is possible that economies of scale in housing may be decreasing, possibly because of negative externalities in production from congestion, regulation, or other sources. It may be more difficult for producers to build new housing in already crowded environments, such as on a lot surrounded by other structures. New construction may impose negative externalities in consumption on incumbent residents, e.g., by blocking views or increasing traffic. Aware of this, residents may seek to constrain housing development to limit these externalities through regulation, lowering housing productivity.

We explore this hypothesis in table 6, which 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 roughly 6 percent are consistent with those in the literature. The results in column 2 reveal negative elasticities, nearly 8 percent in magnitude. According to the results in column 3, which uses only the housing productivity component predicted by the regulatory subindices, about half of this relationship results from greater regulation. Overall productivity, examined in column 4, increases with population, but much more weakly than trade productivity. The results in

[18] Also shown in Figure 4 is a line which depicts the bias to trade productivity estimates if land values are proxied with housing values, assuming housing productivities are uniform across cities (see Albouy 2009). Cities along this line would be inferred to have the same trade productivity, as cities with higher housing productivity have housing values low relative to land values, leading to lower inferred measures of trade productivity.

column 5 suggest that this relationship would be stronger if the greater regulation associated with higher populations were held constant. As we explore in the next section, holding the regulatory environment constant could have negative consequences for urban quality of life.

5.2 Housing Productivity and Quality of Life

The model of section 2 predicts that if the sole effects of regulations were to reduce housing productivity, then they would increase housing prices while reducing land values, unambiguously reducing welfare (Albouy 2009). Ostensibly, the purpose of land-use regulations is to raise housing values by ”recogniz[ing] local externalities, providing amenities that make communities more attractive,” (Quigley and Rosenthal 2005) i.e., by raising demand, rather than by limiting supply, giving rise to terms such as ”externality zoning.” To our knowledge, there are only a few, limited estimates of the benefits of these regulations, e.g. Cheshire and Sheppard (2002) and Glaeser et al. (2005b), both of which suggest that the welfare costs of regulation outweigh the benefits.

To examine this hypothesis we relate our quality-of-life and housing-productivity estimates, shown in figure 5. The regression line in this figure suggests that a one-point decrease in housing productivity is associated with a 0.1-point increase in quality of life. If we accept the relationship as causal, the net welfare benefit of this trade-off, measured as a fraction of total consumption, equals this 0.1-point increase, minus the one-point decrease multiplied by the expenditure share of housing, which we calibrate as 0.18. Thus, a one-point decrease in housing productivity results in a net welfare loss of 0.08-percent of consumption. These results help to rationalize the existence of welfare-reducing regulations, if the benefits accrue to incumbent residents, who control the political process, while the costs are borne by potential residents, who do not have a local political voice.[19]

We explore this relationship further in table 7, which controls for possible confounding factors

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

and isolates housing productivity predicted by regulation. The odd numbered columns include controls for natural amenities, such as climate, adjacency to the coast, and the geographic constraint index; the even numbered columns add controls for artificial amenities, such as the population level, density, education, crime rates, and number of eating and drinking establishments. In columns 1 and 2, these controls undo the relationship, as geographic amenities are related negatively to productivity and positively to quality of life. When we focus on productivity predicted by regulation, in columns 3 and 4, the original relationship is restored, although it is slightly weaker. As before, if these results are interpreted causally, the impact of land-use regulations is on net welfare-reducing.

Non-causal explanations for the relationship in table 7 are also plausible. For instance, residents in areas with unobserved amenities may simply elect to regulate land-use for reasons unrelated to urban quality of life. Alternatively, with preference heterogeneity, the quality-of-life measure represents the willingness-to-pay of the marginal resident. In cities with low-housing productivity, the supply of housing is effectively constrained, raising the willingness-to-pay of the marginal resident, much as in the "Superstar City" hypothesis of Gyourko, Mayer, and Sinai (2006). However, the negative relationship between productivity and quality of life appears to hold for more than a small subset of superstar cities.

6 Conclusion

Our novel index of land values seems to contain important information not captured by typical indices of housing prices. As theory would predict, the variation of land values is greater than that of housing, and ultimately implies an average cost share of land of approximately one-third. The housing-cost model performs surprisingly well at explaining housing prices despite the disparate data sources. Our empirical model is consistent with constant returns to scale at the firm level, with an elasticity of substitution between land and non-land inputs of roughly one-half. This implies that the cost of share land rises from as low as 11 percent in low-value areas to 48 percent in high-value areas.

The housing-cost function modeled above provides the previously untested hypothesis that geographic and regulatory constraints will increase the wedge between the prices of housing and its inputs. The data strongly support this hypothesis and may provide guidance as to which regulations have the greatest impact on housing costs at the metropolitan level. Furthermore, our parsimonious model explains nearly 90 percent of the variation in metropolitan housing prices and our instrumental variable estimates provide reassurance that our ordinary least squares estimates are likely consistent. In general, the plausibility of the indices and the reasonableness of the empirical results are mutually reinforcing.

The pattern of housing productivity across metropolitan areas is also illuminating. Cities that are productive in tradeables sectors tend to be less productive in housing as the two appear to subject to opposite economies of scale. Larger cities have lower housing productivity, much of which seems attributable to greater regulation. These regulatory costs are associated cross-sectionally with a higher quality of life for residents, although this relationship is weak, suggesting that land-use regulations lead to net welfare costs for the economy as a whole.

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Appendix

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

$$\hat{p}_j = \phi^L(\hat{r}_j - \hat{A}_j^{YL}) + (1-\phi^L)(\hat{v}_j - \hat{A}_j^{YM}) + (1/2)\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{A}_j^{YL} - \hat{v}_j + \hat{A}_j^{YM})^2 \tag{A.1}$$

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

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. 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:

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

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 on the estimated wage differentials. All of the wage regressions are at the CMSA level rather than the PMSA level to reflect the ability of workers to commute relatively easily 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.

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 measured price differentials. In contrast to the wage regressions, the housing price regressions were run at the PMSA level rather than the CMSA level to achieve a better geographic match between the housing stock and the underlying land.

C Estimate Stability

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

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

The results in column 7 drop observations that we deemed to have low growth, i.e. metro areas with population growth from 1980 to 2010 in the bottom decile. The estimated cost share of land and the elasticity of substitution using this sample is slightly lower, albeit not significantly. However, in a regression using our favored specification, with all of the regulatory and geographic subindices, not shown, the results are more similar. If, as in column 8, we instead define our low-growth sample using the bottom decile of MSAs in terms of the building permits issued from 2005 to 2010 relative to the size of the housing stock, the results are quite close to our base specification.

TABLE 1: LAND VALUE INDEX REGRESSIONS

	Fraction of Sample	Dependent Variable: Log Price per Acre			
	(0)	(1)	(2)	(3)	(4)
Log lot size (acres)			-0.660	-0.647	-0.597
			(0.002)	(0.002)	(0.003)
No proposed use	15.9%			-0.198	-0.332
				(0.012)	(0.014)
Proposed use: commercial	0.3%			-0.369	-0.252
				(0.064)	(0.077)
Proposed use: industrial	7.5%			-0.316	-0.522
				(0.015)	(0.019)
Proposed use: retail	8.1%			0.260	0.211
				(0.014)	(0.017)
Proposed use: single-family	10.7%			-0.020	-0.188
				(0.014)	(0.020)
Proposed use: multi-family	3.3%			-0.071	-0.174
				(0.021)	(0.019)
Proposed use: office	6.3%			0.072	0.185
				(0.016)	(0.020)
Proposed use: apartment	3.6%			0.468	0.366
				(0.021)	(0.016)
Proposed use: hold for development	19.2%			-0.069	-0.085
				(0.013)	(0.013)
Proposed use: hold for investment	4.3%			-0.358	-0.287
				(0.020)	(0.027)
Proposed use: mixed use	1.7%			0.373	0.407
				(0.028)	(0.027)
Proposed use: medical	1.0%			0.162	-0.038
				(0.038)	(0.051)
Proposed use: parking	0.9%			0.181	0.253
				(0.039)	(0.033)
Number of Observations		68,757	68,757	68,757	68,757
Adjusted R-squared		0.301	0.699	0.711	0.762
Weighted by Predicted Density		No	No	No	Yes

Robust standard errors, clustered by MSA/PMSA, reported in parentheses. Land-value data from CoStar COMPS database for years 2005 to 2010. All specifications include a full set of interacted MSA and year-of-sale indicator (not shown). Predicted density is number of land sales predicted by a geographical model of housing units relative to city center; please see section 3.1, Land Values, for a full description.

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

Name of Area	Population	Observed No. of Land Sales	Land Value	Housing Price	Wages (Const. Only)	Const. Price Index	Regulation Index (z-score)	Geo Avail. Index (z-score)	Land Value Rank
Metropolitan Areas:									
New York, NY PMSA	9,747,281	1,603	1.67	0.84	0.25	0.31	0.66	0.56	1
San Francisco, CA PMSA	1,785,097	152	1.49	1.29	0.21	0.23	0.77	2.17	3
San Jose, CA PMSA	1,784,642	217	1.31	1.08	0.21	0.18	-0.02	1.71	4
Orange County, CA PMSA	3,026,786	233	1.24	0.93	0.12	0.10	0.20	1.15	5
Los Angeles-Long Beach, CA PMSA	9,848,011	1,760	1.00	0.86	0.12	0.10	0.38	1.15	7
Washington, DC-MD-VA-WV PMSA	5,650,154	1,840	0.71	0.39	0.18	0.01	0.30	-0.74	16
Boston, MA-NH PMSA	3,552,421	122	0.52	0.62	0.10	0.18	2.18	0.24	21
Chicago, IL PMSA	8,710,824	3,511	0.24	0.14	0.06	0.17	-0.32	0.54	35
Phoenix-Mesa, AZ MSA	4,364,094	5,946	0.23	-0.03	-0.01	-0.10	0.64	-0.74	37
Philadelphia, PA-NJ PMSA	5,332,822	859	0.12	0.02	0.05	0.16	1.31	-0.93	43
Riverside-San Bernardino, CA PMSA	4,143,113	2,452	0.02	0.22	0.12	0.07	0.47	0.44	51
Atlanta, GA MSA	5,315,841	5,229	-0.16	-0.32	0.03	-0.10	-0.29	-1.23	74
Houston, TX PMSA	5,219,317	1,143	-0.37	-0.54	0.04	-0.12	-0.92	-1.01	107
Dallas, TX PMSA	4,399,895	811	-0.40	-0.46	0.00	-0.14	-0.69	-0.98	114
Detroit, MI PMSA*	4,373,040	679	-0.45	-0.35	-0.04	0.05	-0.27	-0.22	118
Saginaw-Bay City-Midland, MI MSA*	390,032	41	-1.74	-0.63	-0.16	-0.03	-0.35	-0.62	213
Utica-Rome, NY MSA*	293,280	15	-1.82	-0.58	-0.27	-0.05	-1.20	-0.56	214
Rochester, NY MSA*	1,093,434	110	-1.89	-0.54	-0.07	0.01	-0.42	0.07	215
Metropolitan Population:									
Less than 500,000	30,837,205	5,017	-0.53	-0.22	-0.08	-0.39	-0.03	-0.05	4
500,000 to 1,500,000	55,777,644	13,942	-0.42	-0.20	-0.07	-0.26	-0.16	-0.06	3
1,500,000 to 5,000,000	89,173,333	32,032	0.15	0.07	0.01	0.11	0.17	0.01	2
5,000,000+	49,824,250	15,945	0.61	0.31	0.11	0.20	0.01	0.10	1
Standard Deviations (pop. wtd.)			0.76	0.51	0.16	0.96	1.01	0.14	
Correlation with land values (pop. wtd.)			1.00	0.89	0.66	0.61	0.52	0.57	

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

TABLE 3: MODEL OF HOUSING COSTS WITH AGGREGATE GEOGRAPHIC AND REGULATORY INDICES

Specification	Basic Cobb-Douglas (1)	Restricted Cobb-Douglas (2)	Translog (3)	Restricted Translog (4)	Restricted Cobb-Douglas (Instr. Var.) (5)	Restricted Translog (Instr. Var.) (6)	Non-neutral Productivity Translog (7)	Restricted Translog w/ Constr Wages (8)
Land-Value Differential	0.365	0.372	0.348	0.374	0.427	0.342	0.373	0.352
	(0.040)	(0.039)	(0.042)	(0.042)	(0.081)	(0.097)	(0.041)	(0.038)
Construction-Price Differential	0.965	0.628	0.887	0.626	0.573	0.658	0.627	0.648
	(0.170)	(0.039)	(0.177)	(0.042)	(0.081)	(0.097)	(0.041)	(0.038)
Land-Value Differential Squared			0.034	0.074		0.091	0.062	0.072
			(0.036)	(0.040)		(0.113)	(0.042)	(0.036)
Construction-Price Differential Squared			-1.095	0.074		0.091	0.062	0.072
			(1.145)	(0.040)		(0.113)	(0.042)	(0.036)
Land-Value Differential X Construction-Price Differential			0.384	-0.148		-0.182	-0.124	-0.144
			(0.367)	(0.080)		(0.226)	(1.077)	(0.072)
Geographic Constraint Index: z-score	0.091	0.099	0.091	0.089	0.083	0.095	0.088	0.107
	(0.027)	(0.028)	(0.026)	(0.029)	(0.042)	(0.035)	(0.025)	(0.027)
Regulatory Index: z-score	0.060	0.076	0.075	0.082	0.065	0.090	0.085	0.078
	(0.018)	(0.015)	(0.014)	(0.015)	(0.023)	(0.028)	(0.016)	(0.015)
Geographic Constraint Index times Land Value Differential minus Construction							0.007	
							(0.050)	
Regulatory Index times Land Value Differential minus Construction Price							0.022	
							(0.026)	
Constant	0.001	0.001	-0.016	-0.032	0.001	-0.032	-0.035	-0.031
	(0.024)	(0.025)	(0.039)	(0.029)	(0.024)	(0.010)	(0.028)	(0.026)
Number of Observations	856	856	856	856	206	856	856	888
Number of MSAs	206	206	206	206	206	206	206	215
Adjusted R-squared	0.854	0.848	0.863	0.857	0.799	0.856	0.793	0.847
p -value for CRS restrictions		0.046		0.511				0.019
p -value for CD restrictions	0.552	0.149						
p- value for all restrictions		0.126						
Elasticity of Substitution	1.000	1.000		0.367	1.000	0.189	0.470	0.371
				(0.321)		(1.074)	(0.347)	(0.296)
p-value from Chi-squared test of regressor endogeneity					0.571	0.674		

Dependent variable in all regressions is the housing price index. Robust standard errors, clustered by CMSA, reported in parentheses. Data sources are described in Table 2. Restricted model specifications require that the production function exhibits constant returns to scale (CRS). Cobb-Douglas (CD) restrictions impose that the squared and interacted differential coefficients equal zero (the elasticity of substitution between factors equals 1). Instrumental variables are the inverse mean distance from the sea and average winter temperature; first-stage regressions are reported in table A1.

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

Specification	Regulatory Index Factor Loading			Restricted Translog w Cons Price
Dependent Variable		Reg Index	Geo Index	Hous. Price
	(1)	(2)	(3)	(4)
Land-Value Differential				0.326
				(0.029)
Land-Value Differential Squared				0.056
				(0.024)
Approval Delay: z-score	0.29	0.489		0.074
		(0.034)		(0.044)
Local Political Pressure: z-score	0.22	0.200		0.055
		(0.061)		(0.033)
State Political Involvement: z-score	0.22	0.373		0.040
		(0.023)		(0.020)
Open Space: z-score	0.18	0.014		-0.001
		(0.007)		(0.003)
Exactions: z-score	0.15	-0.039		0.032
		(0.066)		(0.054)
Local Project Approval: z-score	0.15	0.218		0.004
		(0.017)		(0.018)
Local Assembly: z-score	0.14	0.147		-0.022
		(0.041)		(0.024)
Density Restrictions: z-score	0.09	0.107		-0.049
		(0.065)		(0.040)
Supply Restrictions: z-score	0.02	0.132		0.028
		(0.009)		(0.010)
State Court Involvement: z-score	-0.03	-0.130		0.049
		(0.018)		(0.018)
Local Zoning Approval: z-score	-0.04	-0.093		-0.025
		(0.062)		(0.037)
Flat Land Share: z-score			-0.493	-0.088
			(0.035)	(0.023)
Solid Land Share: z-score			-0.787	-0.069
			(0.059)	(0.022)
Constant		0.000	0.000	-0.024
		(0.020)	(0.042)	(0.023)
Number of Observations		890	890	856
Adjusted R-squared		0.948	0.846	0.894
Elasticity of Substitution				0.488
				(0.207)

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources are described in table 2; constituent components of Wharton Residential Land Use Regulatory Index (WRLURI) are from Gyourko et al (2008). Constituent components of geographical index are from Saiz (2010).

TABLE 5: INFERRED INDICES OF SELECTED METROPOLITAN AREAS, RANKED BY TOTAL AMENITY VALUE

	Housing Productivity				
	Total (Including Indices)	Predicted by Regulation Subindices	Trade Productivity	Quality of Life	Total Amenity Value
	(1)	(2)	(3)	(4)	(5)
Metropolitan Areas:					
New York, NY PMSA	-0.002	-0.058	0.148	0.090	0.184
San Francisco, CA PMSA	-0.578	-0.171	0.200	0.083	0.107
San Jose, CA PMSA	-0.484	-0.047	0.196	0.063	0.101
Orange County, CA PMSA	-0.411	-0.061	0.095	0.089	0.076
Los Angeles-Long Beach, CA PMSA	-0.447	-0.120	0.089	0.072	0.048
Washington, DC-MD-VA-WV PMSA	-0.138	-0.086	0.115	0.019	0.068
Boston, MA-NH PMSA	-0.342	-0.335	0.085	0.030	0.023
Chicago, IL PMSA	0.029	0.090	0.048	0.004	0.040
Phoenix-Mesa, AZ MSA	0.021	-0.092	-0.004	0.016	0.017
Philadelphia, PA-NJ PMSA	0.113	-0.022	0.054	-0.011	0.044
Riverside-San Bernardino, CA PMSA	-0.188	-0.094	0.065	-0.016	-0.008
Atlanta, GA MSA	0.184	0.006	-0.015	-0.022	0.001
Houston, TX PMSA	0.318	0.084	-0.002	-0.051	0.005
Dallas, TX PMSA	0.217	0.104	-0.023	-0.041	-0.017
Detroit, MI PMSA*	0.227	0.005	-0.015	-0.040	-0.008
Saginaw-Bay City-Midland, MI MSA*	0.184	0.009	-0.130	-0.095	-0.145
Utica-Rome, NY MSA*	0.105	0.225	-0.082	-0.108	-0.142
Rochester, NY MSA*	0.108	0.140	-0.121	-0.108	-0.166
Metropolitan Population:					
Less than 500,000	0.013	0.034	-0.061	-0.021	-0.059
500,000 to 1,500,000	0.031	0.029	-0.051	-0.017	-0.045
1,500,000 to 5,000,000	-0.020	-0.019	0.015	0.008	0.014
5,000,000+	-0.034	-0.022	0.072	0.026	0.066
United States	0.234	0.131	0.087	0.045	0.067
		standard deviations (population weighted)			

Housing productivity, in column 1 is calculated from the specification in column 4 of table 4, as the negative of the sum of the regression residual plus the housing price predicted by the WRLURI and Saiz subindices. Housing productivity predicted by regulation is based upon the projection of housing prices on the WRLURI subindices. Trade productivity is calculated as 0.8 times the overall wage differential plus 0.025 times the land-value differential. Refer to section 5 of the text for the calculation of quality-of-life estimates . Quality of life and total amenity value are expressed as a fraction of average pre-tax household income.

TABLE 6: PRODUCTIVITY IN TRADEABLE AND HOUSING SECTORS ACCORDING TO METROPOLITAN POPULATION AND DENSITY

	Dependent Variable				
	Trade Productivity (1)	Housing Productivity (2)	Hous. Prod. Predicted by Regulation (3)	Total Productivity (4)	Total Productivity No Reg. (5)
Panel A: Population					
Log of Population	0.055	-0.075	-0.034	0.022	0.028
	(0.004)	(0.023)	(0.007)	(0.004)	(0.004)
Number of Observations	206	206	206	206	206
Adjusted R-squared	0.646	0.166	0.156	0.436	0.548
Panel B: Population Density					
Weighted Density Differential	0.063	-0.078	-0.042	0.026	0.034
	(0.004)	(0.031)	(0.011)	(0.005)	(0.004)
Number of Observations	206	206	206	206	206
Adjusted R-squared	0.44	0.091	0.121	0.333	0.421

Robust standard errors, clustered by CMSA, reported in parentheses. Trade and housing productivity differentials are calculated as in table 5. Total productivity is calculated as 0.18 times housing productivity plus 0.64 times trade productivity. Weighted density differential is calculated as the population density at the census-tract level, weighted by population.

TABLE 7: QUALITY OF LIFE AND HOUSING PRODUCTIVITY

	Dependent Variable: Quality of Life			
Housing Productivity Measure:	Total Housing Productivity		Housing Productivity Predicted by Regulation	
	(1)	(2)	(3)	(4)
Housing Productivity	0.001	0.035	-0.087	-0.049
	(0.029)	(0.023)	(0.027)	(0.029)
Natural Controls	X	X	X	X
Artificial Controls		X		X
Number of Observations	201	201	201	201
Adjusted R-squared	0.54	0.73	0.57	0.73

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

TABLE A1: INSTRUMENTAL VARIABLES ESTIMATES, FIRST-STAGE REGRESSIONS

Dependent Variable	Land Rent minus Construction Price (1)	Land Rent minus Construction Price (2)	Land Rent minus Construction Price Squared (3)
Geographic Constraint Index: z-score	0.191	0.129	0.078
	(0.057)	(0.054)	(0.065)
Regulatory Index: z-score	0.143	0.168	-0.151
	(0.044)	(0.040)	(0.037)
Inverse of Mean Distance from Sea: z-score	0.237	0.225	0.226
	(0.030)	(0.050)	(0.052)
Mean Winter Temperature: z-score		0.181	-0.092
		(0.045)	(0.060)
Constant	0.003	0.004	0.402
	(0.053)	(0.045)	(0.048)
Number of Observations	206	206	206
Adjusted R-squared	0.486	0.555	0.184
F-statistic of Excluded Instruments	64.0	15.1	17.1
First Stage Regression for	Table 3 Column 5	Table 3 Column 6	Table 3 Column 6

Robust standard errors, clustered by CMSA, in parentheses. Inverse of mean distance from sea and mean winter temperature are from Albouy et al. (2012).

TABLE A2: MODEL OF HOUSING COSTS, ROBUSTNESS ANALYSIS

Specification Dependent Variable	Base Specification Hous. Price (1)	2005-2007 Sample Hous. Price (2)	2008-2010 Sample Hous. Price (3)	Residential Land Sample Hous. Price (4)	Raw Land Values Hous. Price (5)	Unshrunken Land Values Hous. Price (6)	High Population Growth Sample Hous. Price (7)	High Building Permits Sample Hous. Price (8)
Land-Value Differential	0.374	0.366	0.380	0.382	0.270	0.284	0.317	0.381
	(0.042)	(0.047)	(0.041)	(0.020)	(0.014)	(0.040)	(0.039)	(0.036)
Construction-Price Differential	0.626	0.634	0.620	0.618	0.730	0.716	0.683	0.619
	(0.042)	(0.047)	(0.041)	(0.020)	(0.014)	(0.040)	(0.039)	(0.036)
Land-Value Differential Squared	0.074	0.051	0.097	0.131	-0.031	0.056	0.106	0.078
	(0.040)	(0.044)	(0.041)	(.038)	(.019)	(.023)	(0.050)	(0.053)
Construction-Price Differential Squared	0.074	0.051	0.097	0.131	-0.031	0.056	0.106	0.078
	(0.040)	(0.044)	(0.041)	(.038)	(.019)	(.023)	(0.050)	(0.053)
Land-Value Differential X Construction-Price Differential	-0.148	-0.102	-0.194	-0.262	0.062	-0.112	-0.212	-0.156
	(.08)	(.088)	(.082)	(.076)	(.038)	(.046)	(0.100)	(0.106)
Geographic Constraint Index: z-score	0.089	0.115	0.065	0.082	0.094	0.117	0.104	0.085
	(.029)	(.035)	(.025)	(0.011)	(0.011)	(0.034)	(0.031)	(0.029)
Regulatory Index: z-score	0.082	0.098	0.070	0.081	0.094	0.090	0.081	0.078
	(.015)	(.018)	(.015)	(0.008)	(0.007)	(0.016)	(0.014)	(0.015)
Constant	-0.031	-0.041	-0.030	-0.011	0.015	-0.032	-0.026	-0.037
	(0.029)	(0.034)	(0.028)	(0.010)	(0.011)	(0.032)	(0.030)	(0.030)
Number of Observations	853	337	516	678	853	853	754	731
Adjusted R-squared	0.793	0.786	0.812	0.856	0.845	0.744	0.786	0.795
Elasticity of Subsitution	0.367	0.558	0.175	0.447	1.156	0.449	0.019	0.338
	(0.321)	(0.366)	(0.326)	(0.343)	(0.216)	(0.198)	(0.437)	(0.438)

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

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

Full Name	Population	Census Division	Obs. Land Sales	*Adjusted Differentials* Land Value	Land Value (No Wts.)	Housing Price	Wages (All)	Wages (Const. Only)	*Raw Differentials* Reg. Index (z-score)	Geo Avail. Index (z-score)	Const. Price Index	*Productivity* Housing	Tradea-bles	Land Value Rank
Metropolitan Areas:														
New York, NY PMSA	9,747,281	2	1,603	1.673	1.546	0.842	0.152	0.247	0.661	0.561	0.307	-0.002	0.148	1
Jersey City, NJ PMSA	597,924	2	43	1.588	1.457	0.643	0.159	0.262	0.103	0.236	0.118	0.054	0.150	2
San Francisco, CA PMSA	1,785,097	9	152	1.488	1.416	1.287	0.207	0.214	0.769	2.169	0.234	-0.578	0.200	3
San Jose, CA PMSA	1,784,642	9	217	1.307	1.273	1.081	0.207	0.214	-0.018	1.710	0.178	-0.484	0.196	4
Orange County, CA PMSA	3,026,786	9	233	1.235	1.192	0.930	0.087	0.115	0.196	1.153	0.097	-0.411	0.095	5
Stamford-Norwalk, CT PMSA	361,024	1	19	1.103	1.020	0.972	0.157	0.243	-0.326	0.561	0.134	-0.493	0.139	6
Los Angeles-Long Beach, CA PMSA	9,848,011	9	1,760	1.000	0.961	0.862	0.087	0.115	0.384	1.153	0.097	-0.447	0.089	7
Miami, FL PMSA	2,500,625	5	1,233	0.924	0.909	0.288	-0.057	-0.081	1.104	2.341	-0.075	-0.002	-0.018	8
Seattle-Bellevue-Everett, WA PMSA	2,692,066	9	1,626	0.884	0.848	0.420	0.051	0.035	1.013	0.719	0.065	-0.071	0.065	9
Fort Lauderdale, FL PMSA	1,766,476	5	741	0.871	0.863	0.179	-0.057	-0.082	0.763	2.295	-0.099	0.068	-0.020	10
San Diego, CA MSA	3,053,793	9	957	0.869	0.878	0.737	0.061	0.093	0.276	1.691	0.065	-0.395	0.065	11
Oakland, CA PMSA	2,532,756	9	132	0.857	0.781	0.850	0.192	0.186	0.608	1.605	0.171	-0.448	0.175	12
Santa Barbara-Santa Maria-Lompoc, CA MSA	407,057	9	29	0.836	0.746	0.945	0.073	-0.066	0.994	2.802	0.075	-0.612	0.100	13
Ventura, CA PMSA	802,983	9	131	0.737	0.757	0.803	0.086	0.115	1.503	2.489	0.080	-0.506	0.083	14
Las Vegas, NV-AZ MSA	2,141,893	8	2,553	0.732	0.756	-0.014	0.044	-0.063	-1.392	0.150	-0.110	0.199	0.070	15
Washington, DC-MD-VA-WV PMSA	5,650,154	5	1,840	0.714	0.728	0.387	0.132	0.177	0.305	-0.741	0.008	-0.138	0.115	16
Bergen-Passaic, NJ PMSA	1,387,028	2	79	0.692	0.652	0.684	0.152	0.247	0.684	0.561	0.118	-0.382	0.123	17
Nassau-Suffolk, NY PMSA	2,875,904	2	396	0.687	0.663	0.663	0.152	0.247	0.738	0.561	0.307	-0.246	0.123	18
Santa Rosa, CA PMSA	472,102	9	153	0.567	0.584	0.816	0.207	0.214	1.683	1.671	0.133	-0.552	0.177	19
Naples, FL MSA	318,537	5	78	0.547	0.572	0.490	0.008	-0.213	0.104	2.291			0.053	20
Boston, MA-NH PMSA	3,552,421	1	122	0.517	0.497	0.619	0.093	0.101	2.177	0.241	0.179	-0.342	0.085	21
West Palm Beach-Boca Raton, FL MSA	1,279,950	5	321	0.513	0.419	0.133	-0.033	0.046	0.097	1.720	-0.126	-0.051	-0.026	22
Vallejo-Fairfield-Napa, CA PMSA	541,884	9	146	0.437	0.465	0.529	0.207	0.214	1.134	0.990	0.120	-0.320	0.174	23
Tacoma, WA PMSA	796,836	9	539	0.414	0.414	0.080	0.050	0.033	1.822	0.377	0.042	0.070	0.053	24
Newark, NJ PMSA*	2,045,344	2	142	0.401	0.357	0.545	0.159	0.262	0.698	0.073	0.132	-0.345	0.120	25
Sarasota-Bradenton, FL MSA	688,126	5	601	0.398	0.420	0.128	-0.103	-0.061	1.069	1.849	-0.095	-0.070	-0.078	26
Portland-Vancouver, OR-WA PMSA	2,230,947	9	1,191	0.378	0.361	0.141	-0.049	-0.071	0.071	0.419	0.012	-0.025	-0.026	27
San Luis Obispo-Atascadero-Paso Robles, CA MSA	266,971	9	43	0.361	0.267	0.786	0.003	-0.112	1.364	1.810	0.038	-0.659	0.029	28
Orlando, FL MSA	2,082,421	5	1,612	0.347	0.382	-0.116	-0.088	-0.121	0.146	0.350	-0.092	0.156	-0.056	29
Salinas, CA MSA	410,370	9	12	0.306	0.238	0.644	0.113	-0.035	0.098	1.824	0.096	-0.501	0.120	30
Provo-Orem, UT MSA	545,307	8	47	0.294	0.265	-0.201	-0.128	-0.217	-0.019	1.503	-0.140	0.189	-0.081	31
Middlesex-Somerset-Hunterdon, NJ PMSA	1,247,641	2	101	0.289	0.277	0.444	0.152	0.247	1.377	0.561	0.118	-0.288	0.113	32
Tampa-St. Petersburg-Clearwater, FL MSA	2,747,272	5	1,220	0.271	0.288	-0.116	-0.091	-0.140	-0.671	0.621	-0.061	0.146	-0.058	33
Olympia, WA PMSA	250,979	9	250	0.252	0.245	0.095	0.060	0.054	0.539	0.466	0.031	-0.011	0.055	34
Chicago, IL PMSA	8,710,824	3	3,511	0.239	0.259	0.140	0.054	0.058	-0.316	0.541	0.169	0.029	0.048	35
Reading, PA MSA	407,125	2	36	0.230	0.246	-0.259	-0.050	-0.046	0.504	-0.616	0.015	0.323	-0.035	36
Phoenix-Mesa, AZ MSA	4,364,094	8	5,946	0.226	0.296	-0.030	-0.013	-0.014	0.637	-0.741	-0.099	0.021	-0.004	37
Trenton, NJ PMSA	366,222	2	35	0.225	0.258	0.323	0.159	0.262	2.338	-0.847	0.114	-0.193	0.116	38
Baltimore, MD PMSA	2,690,886	5	802	0.203	0.212	0.165	0.131	0.177	2.087	-0.351	-0.061	-0.157	0.102	39
Melbourne-Titusville-Palm Bay, FL MSA	536,357	5	420	0.152	0.189	-0.169	-0.112	-0.065	0.456	1.732	-0.074	0.149	-0.092	40
Stockton-Lodi, CA MSA	674,860	9	163	0.140	0.128	0.224	0.067	0.165	0.563	-0.834	0.079	-0.146	0.041	41
Salt Lake City-Ogden, UT MSA	1,567,650	8	145	0.124	0.104	-0.116	-0.078	-0.159	-0.383	2.113	-0.125	0.053	-0.046	42
Philadelphia, PA-NJ PMSA	5,332,822	2	859	0.124	0.146	0.016	0.062	0.045	1.306	-0.927	0.163	0.113	0.054	43
Fort Myers-Cape Coral, FL MSA	586,908	5	294	0.120	0.140	0.001	-0.078	-0.071	-0.565	1.187	-0.119	-0.062	-0.060	44
Jacksonville, FL MSA	1,301,808	5	793	0.110	0.139	-0.196	-0.076	-0.130	-0.371	0.900	-0.154	0.110	-0.050	45
Grand Junction, CO MSA	146,093	8	21	0.099	0.045	-0.008	-0.146	-0.060	0.367	0.702	-0.091	-0.042	-0.126	46
Reno, NV MSA	414,820	8	57	0.074	0.087	0.182	0.003	-0.178	-0.803	1.328	-0.022	-0.195	0.032	47
Albuquerque, NM MSA	841,428	8	114	0.041	0.020	-0.129	-0.087	-0.195	0.233	-0.854	-0.098	0.054	-0.051	48
Allentown-Bethlehem-Easton, PA MSA	706,374	2	85	0.035	0.037	-0.132	-0.040	0.079	-0.306	-0.401	0.056	0.159	-0.049	49
Wilmington-Newark, DE-MD PMSA	635,430	5	107	0.021	0.051	-0.030	0.062	0.045	0.377	-0.705	0.059	0.057	0.052	50
Riverside-San Bernardino, CA PMSA	4,143,113	9	2,452	0.016	0.054	0.219	0.087	0.115	0.465	0.437	0.072	-0.188	0.065	51
Minneapolis-St. Paul, MN-WI MSA	3,269,814	4	846	0.014	0.012	-0.042	0.024	-0.011	-0.074	-0.481	0.129	0.112	0.025	52
Lawrence, MA-NH PMSA	413,626	1	29	0.012	-0.028	0.338	0.099	0.121	1.920	0.241	0.135	-0.266	0.075	53
Denver, CO PMSA	2,445,781	8	2,015	0.006	0.000	-0.002	-0.010	0.003	0.968	-0.604	-0.038	-0.043	-0.009	54
Kenosha, WI PMSA	165,382	3	58	0.001	0.041	-0.125	0.059	0.068	0.962	0.929	0.011	0.110	0.046	55
Fort Pierce-Port St. Lucie, FL MSA	406,296	5	71	-0.012	-0.017	-0.084	-0.075	-0.191	0.343	1.765			-0.042	56
Boulder-Longmont, CO PMSA	311,786	8	183	-0.013	0.001	0.204	-0.010	0.003	3.626	0.695	-0.088	-0.288	-0.010	57
Modesto, CA MSA	510,385	9	142	-0.020	-0.028	0.120	0.041	0.044	0.040	-0.724	0.080	-0.095	0.031	58
Daytona Beach, FL MSA	587,512	5	93	-0.036	-0.022	-0.143	-0.135	-0.303	0.393	1.549	-0.106	0.038	-0.082	59

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

				Adjusted Differentials					*Raw Differentials*			*Productivity*		
Full Name	Population	Census Division	Obs. Land Sales	Land Value	Land Value (No Wts.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Avail. Index (z-score)	Const. Price Index	Housing	Tradeables	Land Value Rank
Sioux Falls, SD MSA	224,266	4	17	-0.053	-0.146	-0.556	-0.182	0.181	-1.804	-1.260	-0.188	0.389	-0.202	60
Visalia-Tulare-Porterville, CA MSA	429,668	9	32	-0.061	-0.162	-0.038	-0.016	-0.019	0.362	-0.471			-0.014	61
Raleigh-Durham-Chapel Hill, NC MSA	1,589,388	5	782	-0.077	-0.060	-0.205	-0.042	-0.033	0.427	-1.027	-0.231	0.004	-0.037	62
New Haven-Meriden, CT PMSA	558,692	1	43	-0.100	-0.135	0.291	0.159	0.262	-0.330	0.786	0.108	-0.271	0.108	63
Eugene-Springfield, OR MSA	351,109	9	36	-0.108	-0.173	0.105	-0.154	-0.239	0.187	1.647	0.000	-0.163	-0.112	64
Norfolk-Virginia Beach-Newport News, VA- MSA	1,667,410	5	392	-0.109	-0.092	0.029	-0.078	-0.053	-0.154	1.512	-0.117	-0.164	-0.068	65
Monmouth-Ocean, NJ PMSA	1,217,783	2	124	-0.117	-0.122	0.369	0.152	0.247	2.078	0.561	0.307	-0.211	0.103	66
Huntsville, AL MSA	406,316	6	29	-0.120	-0.115	-0.437	-0.055	-0.177	-2.258	-0.230	-0.147	0.275	-0.028	67
Salem, OR PMSA	396,103	9	54	-0.130	-0.182	-0.050	-0.042	-0.063	0.281	0.199	0.004	-0.009	-0.034	68
Newburgh, NY-PA PMSA	444,061	2	54	-0.132	-0.120	0.169	0.166	0.265	-0.407	0.047	0.163	-0.120	0.113	69
Lakeland-Winter Haven, FL MSA	583,403	5	561	-0.138	-0.080	-0.359	-0.138	-0.201	-0.067	0.156	-0.070	0.246	-0.103	70
Savannah, GA MSA	343,092	5	64	-0.139	-0.144	-0.206	-0.102	-0.168	-1.136	1.528	-0.178	0.018	-0.074	71
Bridgeport, CT PMSA	470,094	1	26	-0.156	-0.253	0.473	0.157	0.254	0.392	0.561	0.107	-0.469	0.105	72
Merced, CA MSA	245,321	9	64	-0.157	-0.139	-0.013	-0.005	0.255	0.636	-0.927			-0.047	73
Atlanta, GA MSA	5,315,841	5	5,229	-0.162	-0.113	-0.325	-0.007	0.033	-0.288	-1.225	-0.098	0.184	-0.015	74
Madison, WI MSA	491,357	3	239	-0.164	-0.150	-0.033	-0.070	-0.180	0.280	-0.869	-0.002	-0.041	-0.042	75
Brockton, MA PMSA	268,092	1	22	-0.166	-0.170	0.329	0.097	0.096	3.044	0.241	0.121	-0.319	0.073	76
Colorado Springs, CO MSA	604,542	8	892	-0.170	-0.198	-0.231	-0.134	-0.150	0.987	-0.331	-0.070	0.110	-0.108	77
Janesville-Beloit, WI MSA	160,155	3	15	-0.184	-0.255	-0.382	-0.172	-0.046	-0.758	-1.190	-0.017	0.288	-0.160	78
Hamilton-Middletown, OH PMSA	363,184	3	151	-0.203	-0.172	-0.466	-0.052	-0.040	-0.301	-1.083	-0.088	0.319	-0.048	79
Medford-Ashland, OR MSA	201,286	9	12	-0.205	-0.338	0.286	-0.164	-0.046	0.957	2.003	0.004	-0.372	-0.153	80
Lincoln, NE MSA	281,531	4	24	-0.217	-0.264	-0.444	-0.212	-0.189	0.824	-1.348	-0.115	0.272	-0.177	81
Bremerton, WA PMSA	240,862	9	18	-0.217	-0.249	0.238	0.060	0.063	0.536	1.124	0.065	-0.285	0.042	82
Fargo-Moorhead, ND-MN MSA	200,102	4	13	-0.227	-0.378	-0.515	-0.188	-0.340	-2.275	-1.281	-0.164	0.307	-0.131	83
Tucson, AZ MSA	1,020,200	8	1,749	-0.228	-0.230	-0.071	-0.123	-0.178	1.978	-0.292	-0.134	-0.115	-0.095	84
Fort Collins-Loveland, CO MSA	298,382	8	344	-0.231	-0.216	-0.079	-0.116	-0.216	0.920	0.110	-0.085	-0.073	-0.083	85
Champaign-Urbana, IL MSA	195,671	3	22	-0.237	-0.273	-0.387	-0.130	-0.289	-0.934	-1.355	0.046	0.321	-0.084	86
Rocky Mount, NC MSA	146,596	5	12	-0.244	-0.382	-0.643	-0.100	-0.275	-1.123	-0.519	-0.314	0.328	-0.058	87
Lexington, KY MSA	554,107	6	29	-0.249	-0.303	-0.421	-0.156	-0.100	-0.052	-1.136	-0.119	0.238	-0.138	88
New Orleans, LA MSA*	1,211,035	7	66	-0.249	-0.292	-0.194	-0.057	-0.156	-2.227	2.255	-0.110	0.018	-0.036	89
Danbury, CT PMSA	223,095	1	23	-0.273	-0.336	0.511	0.149	0.255	-0.600	0.561	0.307	-0.396	0.095	90
Nashville, TN MSA	1,495,419	6	455	-0.275	-0.252	-0.267	-0.066	-0.095	-0.956	-0.795	-0.118	0.078	-0.055	91
Atlantic-Cape May, NJ PMSA	367,803	2	37	-0.286	-0.307	0.246	0.074	0.055	0.713	1.778	0.102	-0.284	0.055	92
Asheville, NC MSA	251,894	5	41	-0.287	-0.302	-0.021	-0.174	-0.229	-1.268	1.891	-0.263	-0.273	-0.136	93
Lafayette, IN MSA	202,331	3	13	-0.289	-0.297	-0.571	-0.207	-0.454	-0.862	-0.147	-0.089	0.395	-0.133	94
Springfield, MA MSA*	609,993	1	28	-0.302	-0.362	0.058	-0.011	-0.007	0.702	-0.095	0.052	-0.138	-0.017	95
South Bend, IN MSA	267,613	3	12	-0.313	-0.410	-0.641	-0.182	0.057	-2.228	-0.907	-0.079	0.464	-0.189	96
Fresno, CA MSA	1,063,899	9	137	-0.337	-0.304	0.074	-0.013	-0.034	1.048	-0.793	0.082	-0.141	-0.016	97
Billings, MT MSA	144,797	8	25	-0.345	-0.383	-0.261	-0.198	-0.441	-0.632	-0.868	-0.094	0.065	-0.128	98
Austin-San Marcos, TX MSA	1,705,075	7	384	-0.347	-0.295	-0.303	-0.049	-0.069	-0.769	-1.241	-0.208	0.029	-0.045	99
Dutchess County, NY PMSA	293,562	2	33	-0.348	-0.304	0.325	0.170	0.262	0.205	0.561	0.163	-0.338	0.112	100
Worcester, MA-CT PMSA	547,274	1	56	-0.351	-0.359	0.191	0.093	0.101	3.051	0.241	0.111	-0.240	0.063	101
Columbus, OH MSA	1,718,303	3	671	-0.357	-0.319	-0.395	-0.058	-0.040	0.060	-1.303	-0.045	0.231	-0.058	102
Richland-Kennewick-Pasco, WA MSA	245,649	9	27	-0.357	-0.397	-0.318	0.022	0.146	0.866	-0.823	-0.036	0.160	-0.010	103
Cleveland-Lorain-Elyria, OH PMSA*	2,192,053	3	416	-0.358	-0.340	-0.417	-0.084	-0.115	-0.576	0.565	0.010	0.291	-0.070	104
Greeley, CO PMSA	254,759	8	320	-0.361	-0.303	-0.305	-0.010	0.002	-0.431	-0.930	-0.153	0.068	-0.019	105
Charleston-North Charleston, SC MSA	659,191	5	214	-0.367	-0.352	-0.085	-0.111	-0.107	-1.566	1.545	-0.188	-0.182	-0.098	106
Houston, TX PMSA	5,219,317	7	1,143	-0.367	-0.336	-0.539	0.014	0.036	-0.924	-1.013	-0.120	0.318	-0.002	107
Chattanooga, TN-GA MSA	510,388	6	51	-0.372	-0.373	-0.399	-0.141	-0.219	-1.436	-0.157	-0.147	0.158	-0.109	108
Richmond-Petersburg, VA MSA	1,119,459	5	399	-0.377	-0.354	-0.126	-0.012	-0.072	-0.913	-0.993	-0.122	-0.096	-0.010	109
La Crosse, WI-MN MSA	132,923	3	21	-0.388	-0.435	-0.334	-0.154	-0.258	0.293	0.333	-0.050	0.156	-0.116	110
Cincinnati, OH-KY-IN PMSA	1,776,911	3	637	-0.391	-0.366	-0.395	-0.052	-0.040	-1.262	-0.920	-0.073	0.203	-0.053	111
Gary, IN PMSA*	657,809	3	111	-0.394	-0.412	-0.425	0.060	0.068	-1.396	0.124	0.035	0.306	0.036	112
York, PA MSA	428,937	2	47	-0.396	-0.383	-0.217	-0.022	-0.107	0.991	-0.831	-0.020	0.057	-0.014	113
Dallas, TX PMSA	4,399,895	7	811	-0.403	-0.381	-0.461	-0.014	0.000	-0.692	-0.976	-0.140	0.217	-0.023	114
McAllen-Edinburg-Mission, TX MSA	741,152	7	61	-0.405	-0.409	-0.959	-0.205	-0.136	-1.021	-1.380	-0.261	0.629	-0.183	115
Hagerstown, MD PMSA	145,910	5	28	-0.415	-0.403	-0.033	0.136	0.171	0.171	-0.505	-0.270	-0.305	0.092	116
Fayetteville-Springdale-Rogers, AR MSA	425,685	7	43	-0.426	-0.410	-0.361	-0.118	-0.152	-0.953	-0.004	-0.271	0.017	-0.099	117
Detroit, MI PMSA*	4,373,040	3	679	-0.455	-0.442	-0.347	-0.010	-0.037	-0.265	-0.221	0.053	0.227	-0.015	118
Lancaster, PA MSA	507,766	2	57	-0.463	-0.451	-0.186	-0.083	-0.154	0.104	-0.841	-0.061	-0.020	-0.066	119
Boise City, ID MSA	571,271	8	106	-0.466	-0.461	-0.222	-0.136	-0.186	-1.042	0.361	-0.111	-0.019	-0.112	120

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

				Adjusted Differentials					*Raw Differentials*			*Productivity*		
Full Name	Population	Census Division	Obs. Land Sales	Land Value	Land Value (No Wts.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Avail. Index (z-score)	Const. Price Index	Housing	Tradea-bles	Land Value Rank
Fort Walton Beach, FL MSA	178,473	5	14	-0.467	-0.595	-0.201	-0.152	0.283	-0.446	1.457			-0.199	121
Milwaukee-Waukesha, WI PMSA	1,559,667	3	399	-0.468	-0.445	-0.076	-0.031	-0.015	0.360	0.628	0.052	-0.049	-0.039	122
Portsmouth-Rochester, NH-ME PMSA	262,128	1	13	-0.473	-0.545	0.185	0.095	0.171	1.448	0.241	-0.037	-0.377	0.052	123
Myrtle Beach, SC MSA	263,868	5	84	-0.474	-0.493	-0.211	-0.185	-0.128	-1.604	1.614			-0.168	124
Manchester, NH PMSA	212,326	1	23	-0.476	-0.537	0.132	0.095	0.171	1.854	0.241	-0.036	-0.325	0.052	125
Harrisburg-Lebanon-Carlisle, PA MSA	667,425	2	89	-0.478	-0.451	-0.344	-0.068	-0.006	0.440	-0.245	-0.010	0.171	-0.075	126
Galveston-Texas City, TX PMSA	286,814	7	39	-0.488	-0.498	-0.498	0.032	0.063	0.662	2.266	-0.139	0.229	0.009	127
Indianapolis, IN MSA	1,823,690	3	193	-0.514	-0.514	-0.500	-0.065	-0.119	-1.380	-1.355	-0.059	0.282	-0.056	128
Spokane, WA MSA	468,684	9	55	-0.538	-0.578	-0.203	-0.118	-0.148	0.711	-0.082	-0.052	-0.017	-0.102	129
Baton Rouge, LA MSA	685,419	7	99	-0.543	-0.548	-0.350	-0.069	-0.044	-1.577	0.222	-0.148	0.059	-0.072	130
Tulsa, OK MSA	873,304	7	245	-0.547	-0.527	-0.518	-0.129	-0.069	-1.474	-1.117	-0.218	0.177	-0.125	131
Akron, OH PMSA*	699,935	3	169	-0.550	-0.523	-0.444	-0.084	-0.114	-0.234	-1.109	-0.024	0.241	-0.075	132
Bakersfield, CA MSA	807,407	9	64	-0.578	-0.604	-0.083	0.044	-0.102	0.266	-0.236	0.065	-0.062	0.043	133
Louisville, KY-IN MSA	1,099,588	6	126	-0.579	-0.592	-0.366	-0.101	-0.141	-1.046	-0.802	-0.078	0.115	-0.088	134
Fort Worth-Arlington, TX PMSA	2,113,278	7	506	-0.583	-0.572	-0.569	-0.014	0.000	-0.728	-1.185	-0.171	0.252	-0.028	135
Roanoke, VA MSA	243,506	5	23	-0.591	-0.641	-0.267	-0.105	-0.138	-1.182	0.513	-0.159	-0.046	-0.093	136
Johnson City-Kingsport-Bristol, TN-VA MSA	503,010	6	28	-0.598	-0.634	-0.552	-0.217	-0.206	-1.674	1.292	-0.220	0.193	-0.189	137
Dayton-Springfield, OH MSA*	933,312	3	116	-0.599	-0.613	-0.510	-0.119	-0.193	-1.038	-1.375	-0.091	0.244	-0.098	138
Yuba City, CA MSA	165,539	9	13	-0.600	-0.735	-0.217	0.012	-0.066	-0.030	-0.743			0.007	139
Greensboro--Winston Salem--High Point, NC MSA	1,416,374	5	438	-0.602	-0.590	-0.408	-0.124	-0.190	-0.907	-1.273	-0.240	0.037	-0.104	140
Omaha, NE-IA MSA	799,130	4	118	-0.603	-0.618	-0.522	-0.126	-0.065	-1.189	-1.262	-0.092	0.257	-0.124	141
Gainesville, FL MSA	243,574	5	34	-0.605	-0.637	-0.128	-0.148	-0.215	-0.227	-0.669	-0.128	-0.166	-0.122	142
Racine, WI PMSA	200,601	3	80	-0.624	-0.597	-0.177	-0.028	0.024	-0.661	1.233	0.015	-0.014	-0.045	143
Springfield, MO MSA	383,637	4	43	-0.626	-0.643	-0.561	-0.201	-0.260	-1.483	-1.100	-0.097	0.284	-0.166	144
Rockford, IL MSA	409,058	3	104	-0.630	-0.564	-0.544	-0.089	-0.011	-1.145	-1.319	0.104	0.415	-0.099	145
St. Louis, MO-IL MSA	2,733,694	4	364	-0.655	-0.638	-0.314	-0.039	-0.126	-1.340	-0.881	0.044	0.135	-0.034	146
Hartford, CT MSA	1,231,125	1	101	-0.665	-0.664	0.199	0.090	0.091	0.389	-0.281	0.104	-0.336	0.054	147
El Paso, TX MSA	751,296	7	94	-0.670	-0.699	-0.659	-0.215	-0.182	0.773	-1.174	-0.233	0.270	-0.192	148
St. Cloud, MN MSA	189,148	4	17	-0.673	-0.818	-0.370	-0.113	-0.313	-0.512	-0.414	0.103	0.230	-0.076	149
Kansas City, MO-KS MSA	2,005,888	4	477	-0.683	-0.657	-0.458	-0.068	-0.086	-1.546	-1.140	0.049	0.277	-0.069	150
Amarillo, TX MSA	238,299	7	27	-0.685	-0.749	-0.556	-0.176	-0.414	-0.945	-1.254	-0.180	0.202	-0.120	151
Green Bay, WI MSA	247,319	3	49	-0.691	-0.700	-0.327	-0.076	-0.005	0.538	-0.282	-0.029	0.083	-0.089	152
Canton-Massillon, OH MSA*	408,005	3	40	-0.697	-0.735	-0.526	-0.122	0.048	-1.568	-0.808	-0.065	0.254	-0.140	153
Hickory-Morganton-Lenoir, NC MSA	365,364	5	88	-0.716	-0.687	-0.433	-0.201	-0.171	-1.216	-0.395	-0.303	-0.017	-0.181	154
Biloxi-Gulfport-Pascagoula, MS MSA	355,075	6	30	-0.720	-0.779	-0.449	-0.127	-0.019	-1.849	1.134	-0.177	0.088	-0.135	155
Brazoria, TX PMSA	309,208	7	62	-0.738	-0.730	-0.544	0.035	0.056	-1.127	-1.013	-0.120	0.221	0.006	156
Memphis, TN-AR-MS MSA	1,230,253	6	173	-0.745	-0.726	-0.529	-0.050	-0.075	1.464	-0.827	-0.136	0.194	-0.055	157
Knoxville, TN MSA	785,490	6	193	-0.801	-0.779	-0.410	-0.156	-0.175	-0.904	0.468	-0.200	0.011	-0.140	158
Ann Arbor, MI PMSA	630,518	3	136	-0.803	-0.762	-0.231	-0.010	-0.036	0.209	-0.949	0.019	-0.003	-0.024	159
Portland, ME MSA	256,178	1	25	-0.806	-0.881	0.135	-0.079	-0.156	1.658	1.005	-0.083	-0.448	-0.071	160
San Antonio, TX MSA	1,928,154	7	348	-0.809	-0.800	-0.592	-0.126	-0.136	-0.662	-1.270	-0.187	0.202	-0.118	161
Wichita, KS MSA	589,195	4	54	-0.828	-0.889	-0.643	-0.112	-0.183	-2.148	-1.345	-0.176	0.255	-0.099	162
Lake Charles, LA MSA	187,554	7	14	-0.830	-0.925	-0.606	-0.079	0.268	-1.936	0.980	-0.189	0.207	-0.136	163
Little Rock-North Little Rock, AR MSA	657,416	7	110	-0.846	-0.849	-0.459	-0.116	-0.181	-1.631	-0.752	-0.155	0.083	-0.103	164
Des Moines, IA MSA	536,664	4	99	-0.862	-0.855	-0.370	-0.079	-0.036	-1.618	-1.123	-0.111	0.023	-0.090	165
Pittsburgh, PA MSA*	2,287,106	2	240	-0.873	-0.844	-0.543	-0.097	-0.118	-0.187	0.050	0.016	0.295	-0.096	166
Fort Wayne, IN MSA	528,408	3	39	-0.874	-0.871	-0.687	-0.142	-0.142	-2.197	-1.300	-0.104	0.342	-0.134	167
Cedar Rapids, IA MSA	209,226	4	33	-0.881	-0.946	-0.490	-0.124	-0.159	-0.965	-1.252	-0.087	0.155	-0.115	168
Oklahoma City, OK MSA	1,213,704	7	395	-0.895	-0.905	-0.552	-0.154	-0.276	-0.857	-1.305	-0.174	0.155	-0.125	169
Jackson, MS MSA	483,852	6	43	-0.924	-0.940	-0.525	-0.091	-0.138	-1.450	-0.869	-0.152	0.132	-0.088	170
Birmingham, AL MSA	997,770	6	148	-0.928	-0.943	-0.401	-0.071	-0.141	-0.695	-0.720	-0.112	0.047	-0.069	171
Brownsville-Harlingen-San Benito, TX MSA	396,371	7	52	-0.928	-0.954	-0.957	-0.239	-0.280	-1.795	-0.068			-0.206	172
Wausau, WI MSA	131,612	3	16	-0.931	-1.013	-0.448	-0.132	-0.040	-0.134	-0.843	-0.059	0.123	-0.142	173
Greenville-Spartanburg-Anderson, SC MSA	1,096,009	5	507	-0.946	-0.923	-0.482	-0.126	-0.174	-1.763	-0.794	-0.251	0.008	-0.116	174
Scranton--Wilkes-Barre--Hazleton, PA MSA*	614,565	2	27	-0.956	-1.006	-0.505	-0.147	-0.257	-0.325	-0.011	0.018	0.235	-0.124	175
Augusta-Aiken, GA-SC MSA	516,357	5	66	-0.956	-0.971	-0.500	-0.104	-0.102	-2.002	-0.913	-0.166	0.089	-0.107	176
Fayetteville, NC MSA	315,207	5	25	-0.960	-1.000	-0.577	-0.191	-0.259	-1.112	-0.663	-0.228	0.118	-0.165	177
Pensacola, FL MSA	455,102	5	102	-0.962	-0.980	-0.338	-0.173	-0.162	-1.644	1.158	-0.136	-0.051	-0.163	178
Tyler, TX MSA	204,665	7	13	-0.969	-1.057	-0.543	-0.146	-0.862	-0.099	-0.930	-0.203	0.098	-0.030	179
Macon, GA MSA	356,873	5	20	-0.971	-0.989	-0.607	-0.076	-0.097	-1.617	-1.038	-0.171	0.187	-0.081	180
Davenport-Moline-Rock Island, IA-IL MSA*	362,790	4	28	-0.974	-1.018	-0.534	-0.111	0.184	-1.729	-1.201	-0.050	0.207	-0.158	181

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				Adjusted Differentials					*Raw Differentials*			*Productivity*		
Full Name	Population	Census Division	Obs. Land Sales	Land Value	Land Value (No Wts.)	Housing Price	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Avail. Index (z-score)	Const. Price Index	Housing	Tradeables	Land Value Rank
Columbia, SC MSA	627,630	5	139	-0.977	-0.983	-0.433	-0.136	-0.141	-1.503	-0.678	-0.234	-0.032	-0.131	182
Lynchburg, VA MSA	232,895	5	13	-0.990	-1.045	-0.407	-0.168	-0.147	-1.596	-0.329	-0.150	-0.002	-0.161	183
Duluth-Superior, MN-WI MSA*	242,041	4	22	-0.993	-1.046	-0.481	-0.149	-0.058	-0.896	0.266	0.075	0.248	-0.157	184
Benton Harbor, MI MSA*	160,472	3	12	-1.011	-1.120	-0.337	-0.142	0.075	-0.979	1.040			-0.171	185
Corpus Christi, TX MSA	391,269	7	74	-1.018	-1.047	-0.634	-0.154	-0.155	-0.711	0.443	-0.229	0.160	-0.147	186
Montgomery, AL MSA	354,108	6	33	-1.031	-1.086	-0.528	-0.136	-0.138	-1.849	-0.897	-0.203	0.071	-0.134	187
Lubbock, TX MSA	270,550	7	45	-1.035	-1.039	-0.629	-0.185	-0.207	-1.811	-1.404	-0.208	0.167	-0.169	188
Bryan-College Station, TX MSA	179,992	7	34	-1.037	-1.058	-0.437	-0.178	-0.634	0.249	-1.110	-0.195	-0.017	-0.097	189
Buffalo-Niagara Falls, NY MSA*	1,123,804	2	104	-1.064	-1.054	-0.595	-0.076	-0.067	-0.646	-0.490	0.034	0.315	-0.089	190
Lafayette, LA MSA	415,592	7	15	-1.082	-1.169	-0.572	-0.118	-0.065	-1.472	-1.327	-0.189	0.113	-0.129	191
Grand Rapids-Muskegon-Holland, MI MSA	1,157,672	3	121	-1.122	-1.144	-0.450	-0.113	-0.176	-0.549	-0.970	-0.121	0.035	-0.108	192
Beaumont-Port Arthur, TX MSA*	378,477	7	60	-1.148	-1.167	-0.733	-0.051	-0.259	-1.309	-0.499	-0.176	0.271	-0.037	193
Killeen-Temple, TX MSA	358,316	7	32	-1.161	-1.187	-0.693	-0.180	-0.219	-1.876	-1.262	-0.259	0.161	-0.166	194
Lansing-East Lansing, MI MSA	453,603	3	40	-1.162	-1.164	-0.453	-0.112	-0.083	-0.043	-1.089	-0.010	0.118	-0.122	195
St. Joseph, MO MSA*	106,908	4	12	-1.163	-1.251	-0.621	-0.112	0.000	-2.636	-1.119	-0.049	0.254	-0.029	196
Kalamazoo-Battle Creek, MI MSA	462,250	3	31	-1.171	-1.175	-0.519	-0.124	-0.110	-0.210	-0.941	-0.061	0.141	-0.129	197
Mobile, AL MSA	591,599	6	135	-1.184	-1.186	-0.465	-0.147	-0.272	-1.860	0.015	-0.154	0.012	-0.127	198
Flint, MI PMSA*	424,043	3	85	-1.187	-1.152	-0.682	-0.010	-0.037	-0.818	-0.955	-0.009	0.344	-0.033	199
Longview-Marshall, TX MSA	222,489	7	14	-1.209	-1.245	-0.621	-0.123	-0.377	-2.295	-0.903	-0.289	0.055	-0.089	200
Erie, PA MSA*	280,291	2	29	-1.304	-1.354	-0.613	-0.163	-0.211	-1.292	1.080	-0.041	0.226	-0.155	201
Appleton-Oshkosh-Neenah, WI MSA	385,264	3	79	-1.311	-1.294	-0.366	-0.090	-0.058	-0.602	-0.544	-0.067	-0.044	-0.109	202
Toledo, OH MSA*	631,275	3	107	-1.325	-1.322	-0.542	-0.096	-0.217	-1.201	-0.494	-0.009	0.179	-0.091	203
Fort Smith, AR-OK MSA	225,132	7	18	-1.344	-1.409	-0.652	-0.222	-0.200	-1.928	-0.454	-0.204	0.125	-0.214	204
Albany-Schenectady-Troy, NY MSA	906,208	2	120	-1.389	-1.369	-0.175	-0.026	-0.067	-0.457	-0.279	-0.003	-0.196	-0.049	205
Peoria-Pekin, IL MSA*	357,144	3	25	-1.425	-1.447	-0.515	-0.060	0.003	-0.913	-1.181	0.045	0.180	-0.092	206
Syracuse, NY MSA*	725,610	2	65	-1.460	-1.456	-0.597	-0.091	-0.040	-1.231	-0.549	-0.015	0.208	-0.116	207
Binghamton, NY MSA*	244,694	2	16	-1.502	-1.571	-0.701	-0.104	0.088	-1.090	0.262	-0.034	0.285	-0.150	208
Youngstown-Warren, OH MSA*	554,614	3	49	-1.515	-1.526	-0.741	-0.169	-0.232	-0.920	-0.909	-0.038	0.321	-0.163	209
Evansville-Henderson, IN-KY MSA	305,455	3	33	-1.539	-1.667	-0.633	-0.136	-0.347	-1.932	-1.000	-0.070	0.187	-0.114	210
Sioux City, IA-NE MSA*	123,482	4	17	-1.678	-1.770	-0.824	-0.227	-0.590	-2.041	-1.276	-0.148	0.284	-0.166	211
Glens Falls, NY MSA	128,774	2	21	-1.707	-1.681	-0.293	-0.131	-0.292	-2.784	0.583	-0.068	-0.182	-0.122	212
Saginaw-Bay City-Midland, MI MSA*	390,032	3	41	-1.744	-1.763	-0.631	-0.118	-0.165	-0.354	-0.620	-0.034	0.184	-0.130	213
Utica-Rome, NY MSA*	293,280	2	15	-1.817	-1.889	-0.577	-0.082	-0.267	-1.199	-0.556	-0.047	0.105	-0.082	214
Rochester, NY MSA*	1,093,434	2	110	-1.891	-1.896	-0.540	-0.089	-0.071	-0.424	0.071	0.007	0.108	-0.121	215
<u>*Census Divisions:*</u>														
New England	8,966,068	1	530	0.042	0.010	0.421	0.092	0.117	1.435	0.240	0.126	-0.330	0.070	5
Middle Atlantic	36,338,768	2	4,567	0.315	0.278	0.260	0.072	0.121	0.537	0.080	0.165	-0.014	0.057	2
East North Central	34,261,505	3	8,520	-0.411	-0.402	-0.272	-0.036	-0.047	-0.529	-0.294	0.031	0.158	-0.037	6
West North Central	12,257,516	4	2,184	-0.501	-0.510	-0.337	-0.061	-0.083	-1.058	-0.897	0.019	0.185	-0.057	7
South Atlantic	41,912,174	5	19,501	0.097	0.109	-0.052	-0.031	-0.032	-0.042	0.177	-0.102	0.011	-0.022	4
East South Central	9,366,975	6	1,473	-0.637	-0.642	-0.421	-0.105	-0.138	-0.834	-0.418	-0.140	0.116	-0.094	9
West South Central	25,989,458	7	4,804	-0.571	-0.565	-0.522	-0.066	-0.081	-0.949	-0.794	-0.164	0.208	-0.064	8
Mountain	15,672,803	8	14,517	0.140	0.157	-0.058	-0.040	-0.084	0.300	-0.046	-0.095	0.026	-0.021	3
Pacific	40,847,165	9	10,840	0.669	0.643	0.604	0.080	0.089	0.514	0.988	0.089	-0.321	0.079	1
<u>*Metropolitan Population:*</u>														
Less than 500,000	30,837,205		5,017	-0.526	-0.556	-0.221	-0.063	-0.077	-0.389	-0.026	-0.054	0.013	-0.061	4
500,000 to 1,500,000	55,777,644		13,942	-0.419	-0.423	-0.204	-0.053	-0.066	-0.261	-0.159	-0.059	0.031	-0.051	3
1,500,000 to 5,000,000	89,173,333		32,032	0.155	0.159	0.072	0.013	0.009	0.106	0.174	0.006	-0.020	0.015	2
5,000,000+	49,824,250		15,945	0.605	0.589	0.314	0.078	0.113	0.197	0.012	0.104	-0.034	0.072	1

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

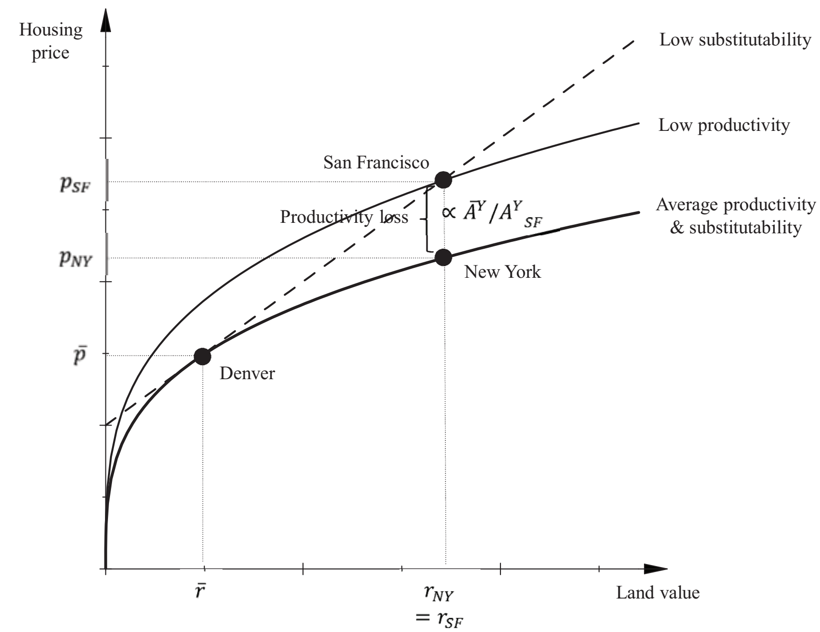

Figure 1B: The effect of low productivity or low substitutability on housing prices in logarithms

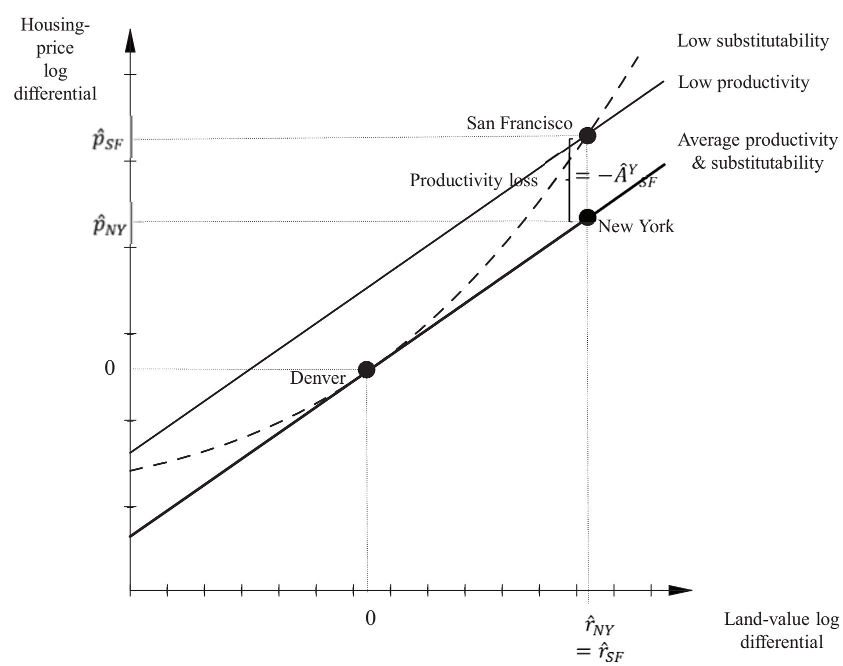

Figure 2: Housing Prices vs. Land Values

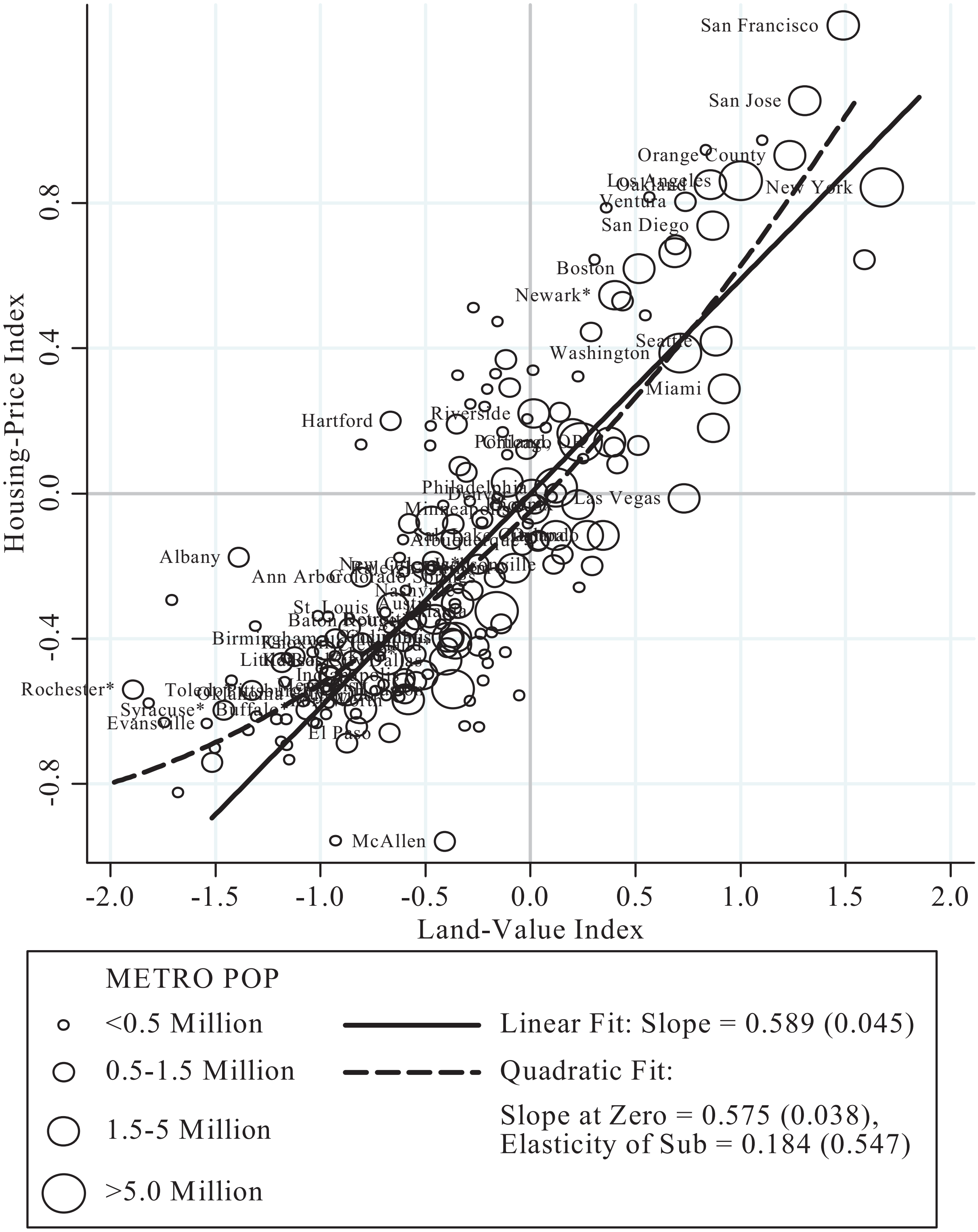

Figure 3A: Construction Prices vs. Land Values

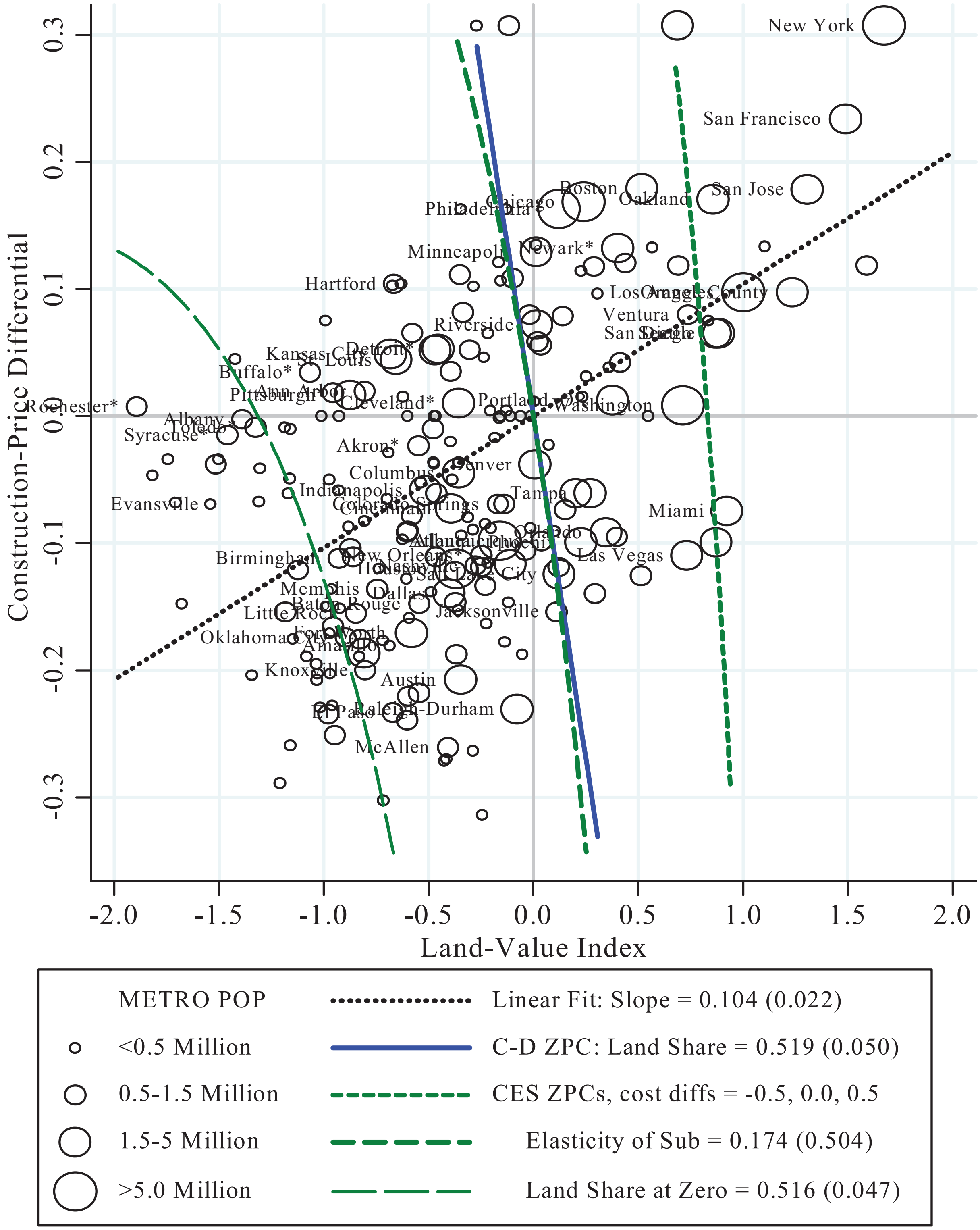

Figure 3B: Three-Dimensional Cost Curve, corresponding to ZPC Curves in Figure 3A, Estimated from Data, No Covariates

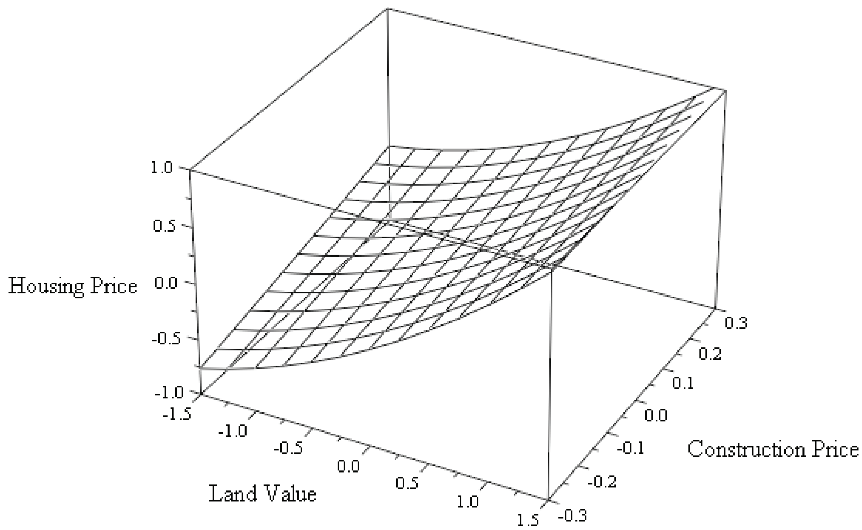

Fig. 4: Productivity in the Tradeable and Housing Sectors

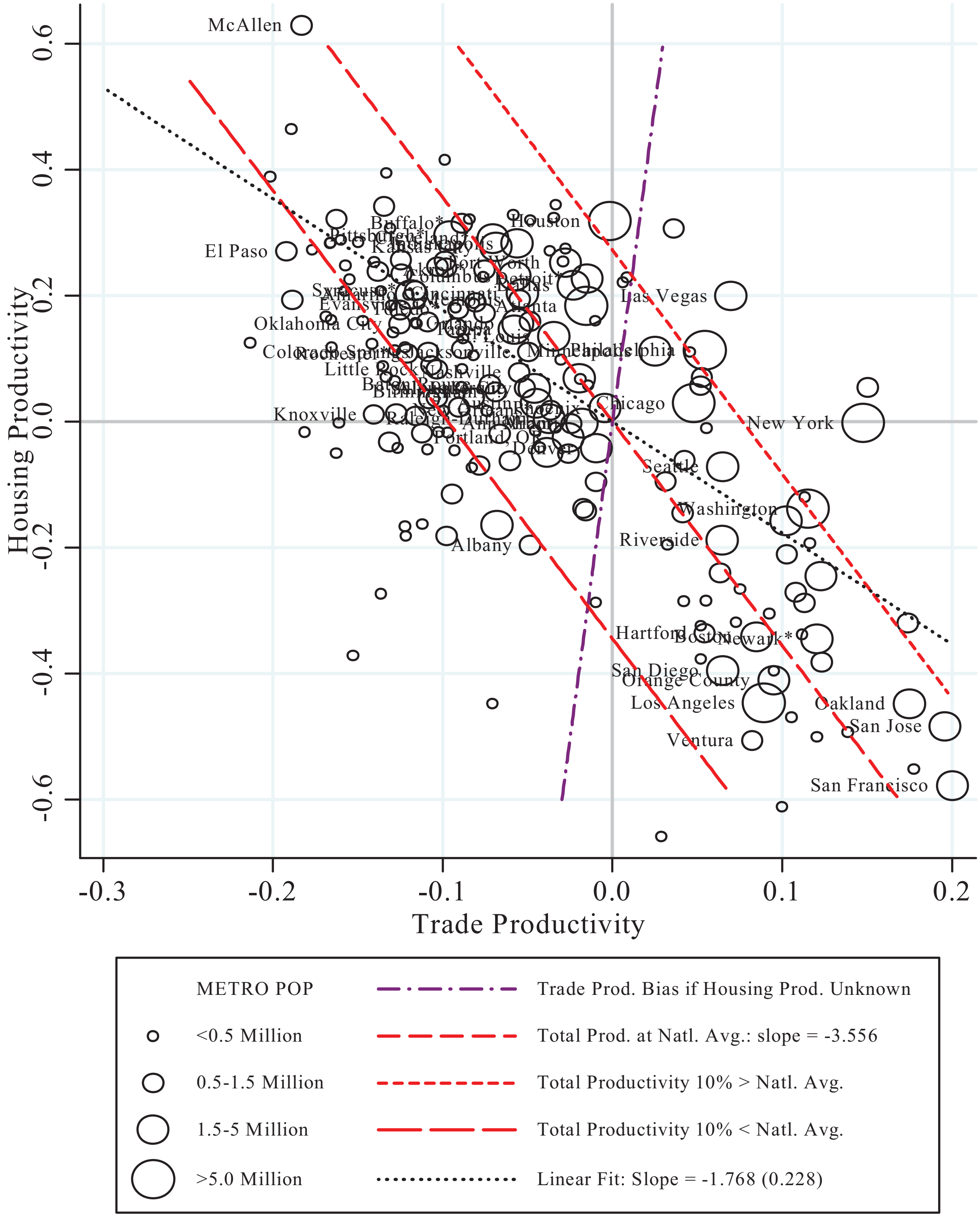

Figure 5: Quality of Life vs. Housing Productivity

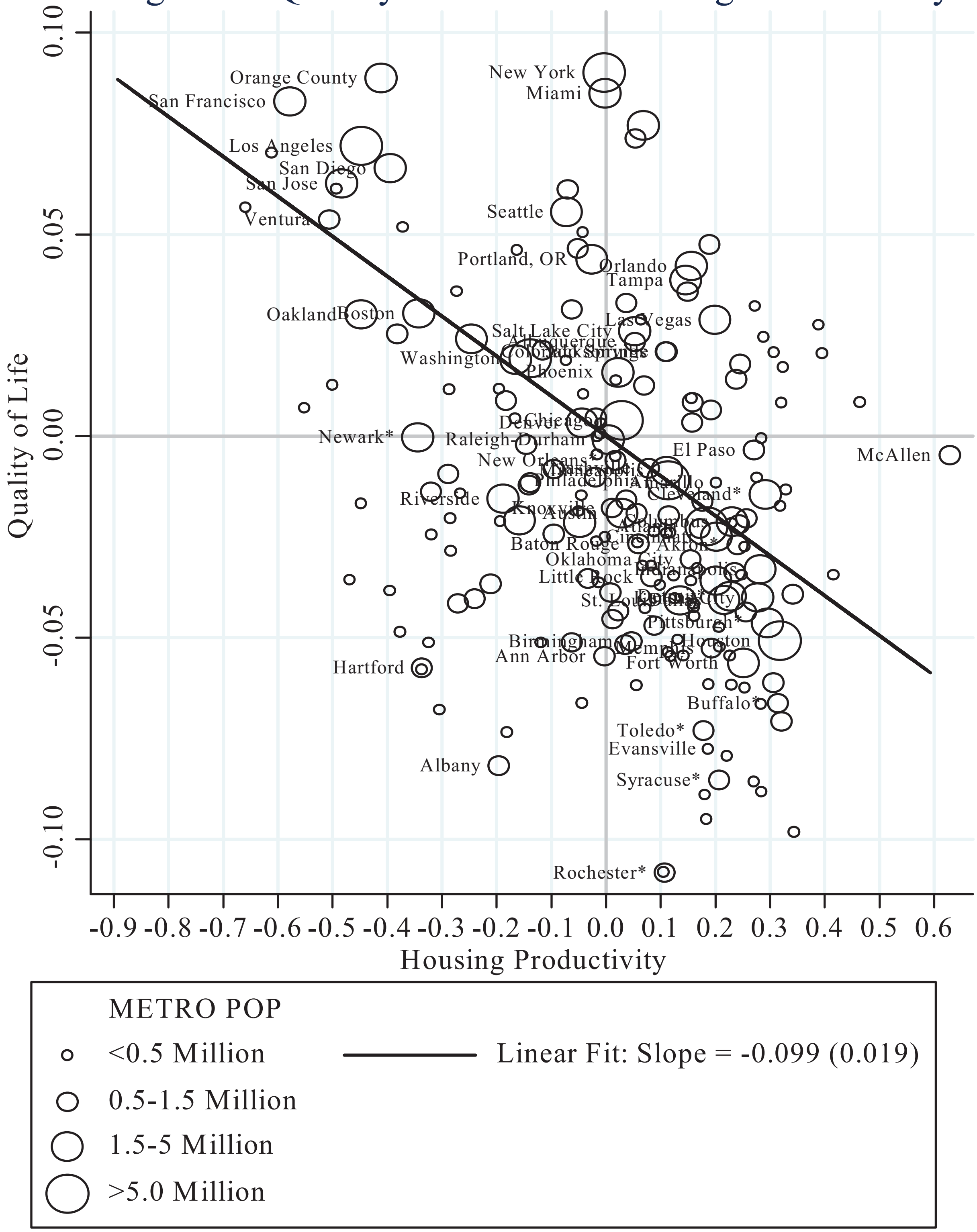

Figure A: Shrunken vs. Unshrunken Land Values

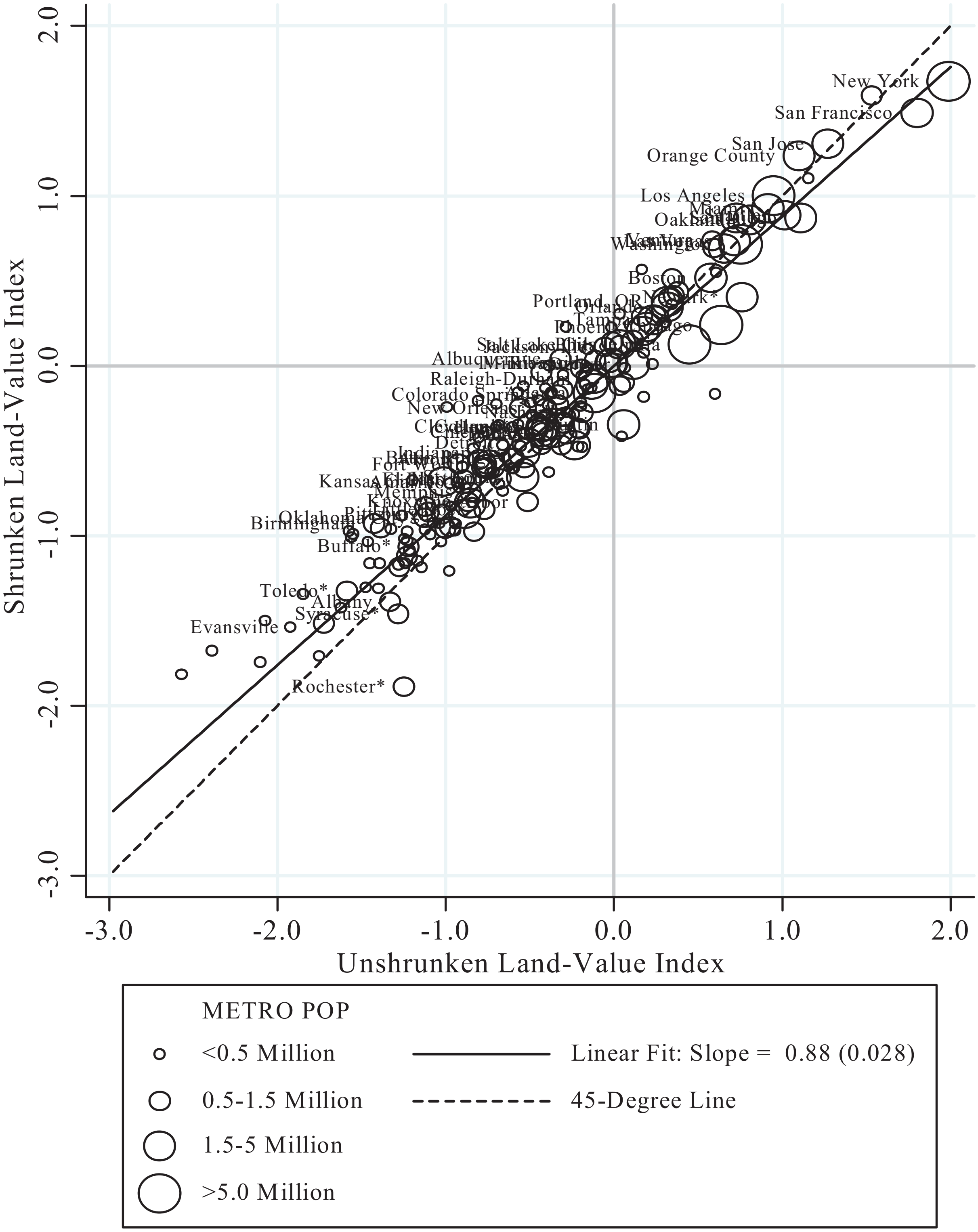

Figure B: Weighted vs. Unweighted Land Values

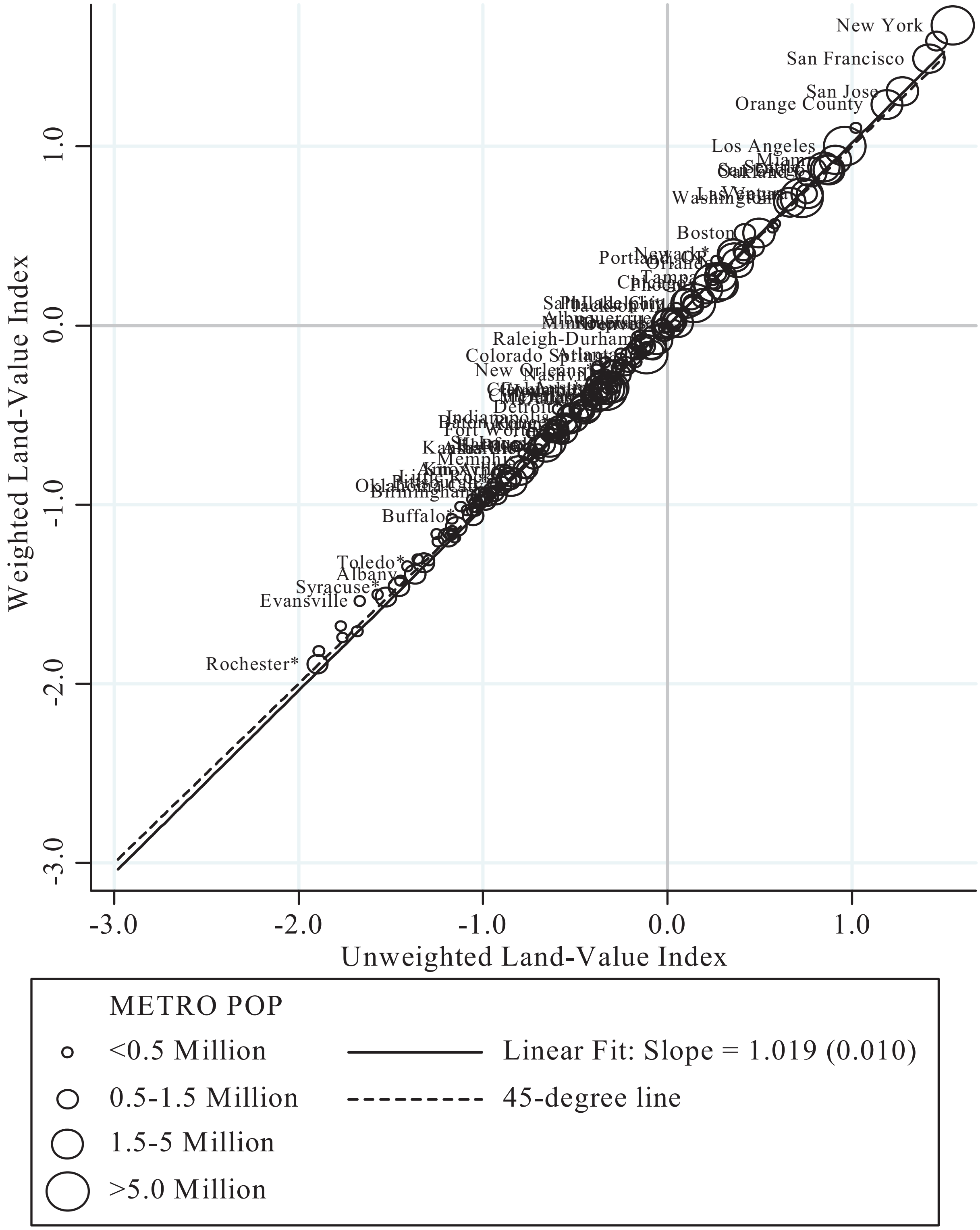

Figure C: Residential vs. Overall Land Values

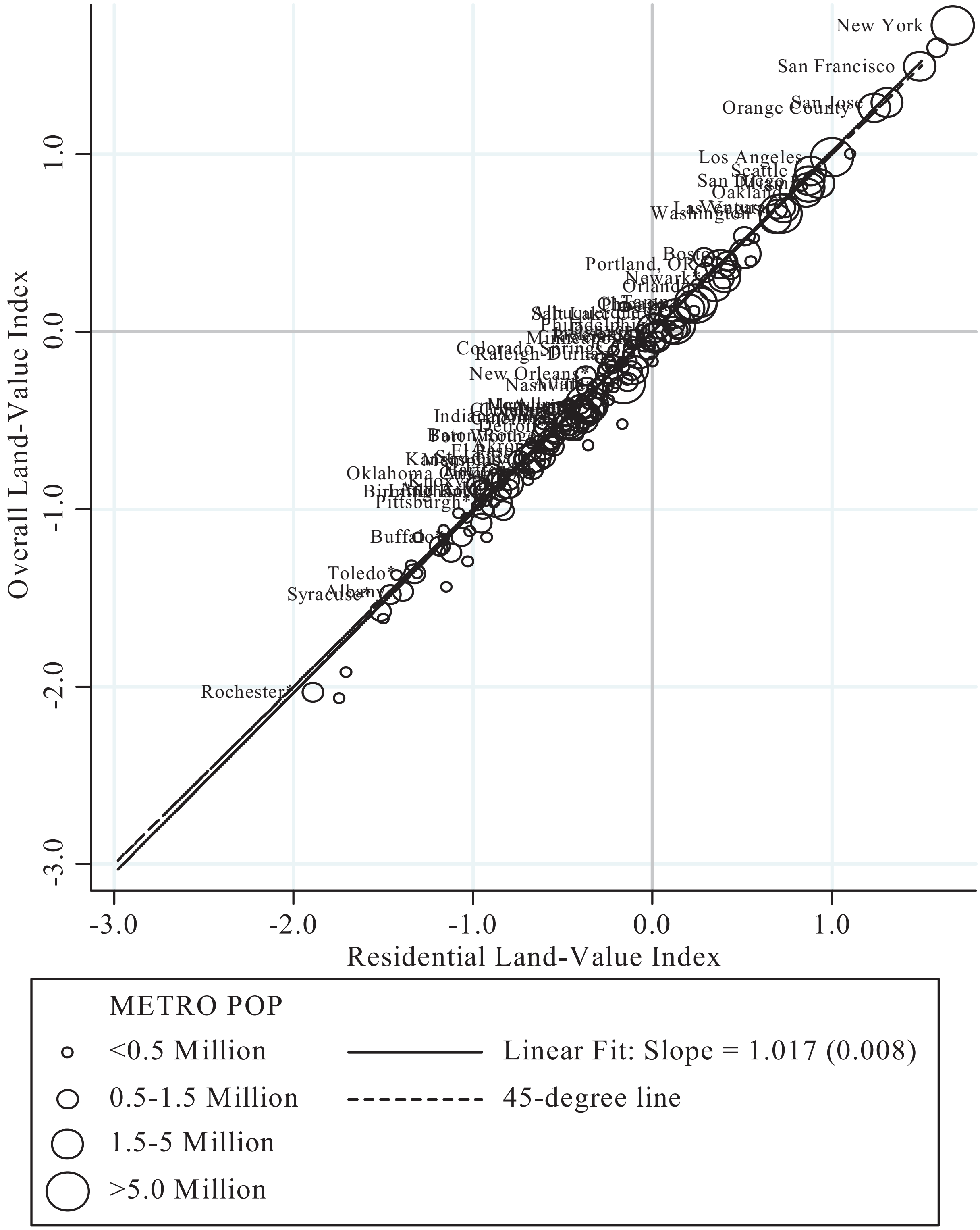

Figure D: Construction Wages vs. Overall Wages

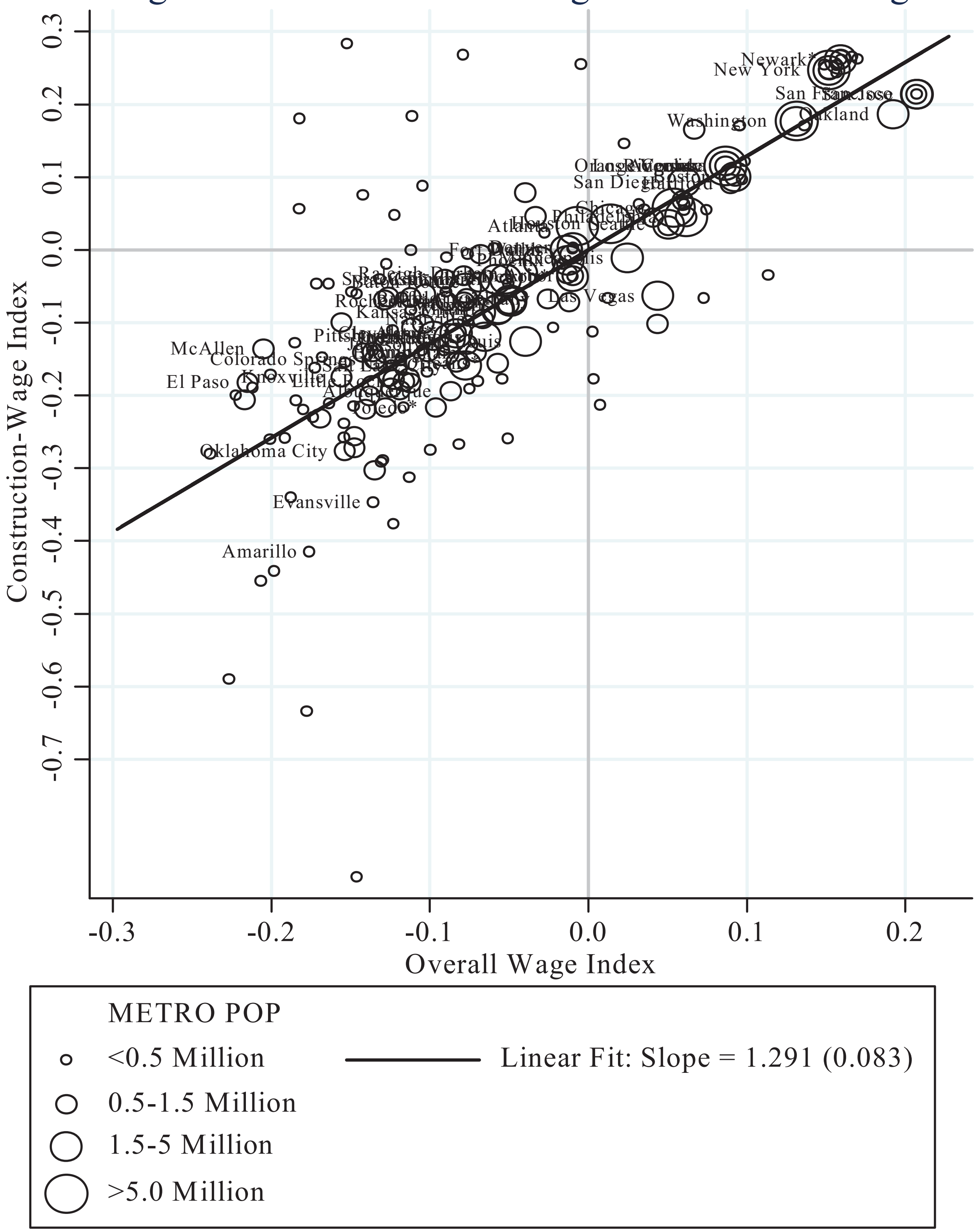

Figure E: Construction Prices vs. Construction Wages