Metropolitan Land Values and Housing Productivity*

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-PRELIMINARY-

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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 costs. Regulatory and geographic constraints, as well as construction costs, are shown to increase the cost of housing relative to land. On average, approximately 22 percent of housing costs are due to land, with an increasing fraction in higher-value areas, implying an elasticity of substitution between land and other inputs of about 0.6. Conditional on land and construction costs, housing productivity is relatively low in larger cities, where productivity in tradables is high. Areas where regulations lower housing productivity have noticeably higher quality-of-life.

1 Introduction

Housing consumption is the largest expenditure item among all goods, and its value depends fundamentally on the land upon which it is built. Land values are extremely heterogenous, reflecting not only land's scarcity, but the many possible advantages and amenities land may provide to households and firms, and its opportunities for development. Although data on housing values is widespread, accurate data on land values have been notoriously piecemeal. 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.

Together with data on housing values, land values allow us to estimate the cost relationship between housing and land and non-land costs using a dual approach (Fuss and McFadden 1978). This supply-side approach to valuing housing strongly complements the demand-side approach to studying differences in housing costs, which is based on how housing provides access to local amenities and labor-market opportunities. It also provides a new measure of local productivity in the housing sector, determined by the difference between the observed value of housing and the value predicted by land and other input costs. This measure of housing productivity provides the most important indicator of a city's efficiency in producing goods that cannot be traded across cities, and can be contrasted with measures of productivity in the tradeables sector. Using recent measures by Gyourko, Saiz, and Summers (2008) and Saiz (2010), we investigate how local housing productivity is influenced by artificial and natural constraints to development due to regulation and geography.

We find that, on average, approximately 22 percent of housing costs are due to land: this share ranges from 0.10 to 0.35 in low to high-value areas, implying an elasticity of substitution between land and other inputs in production on average of about 0.6 in our baseline specification. Consistent estimation of these parameters requires controlling for regulatory and geographic constraints: a standard deviation increase in either basic constraint measure increases housing costs by 9 to 14 percent. We also examine the role of disaggregated measures of regulation and find that approval delays and state and local political and court involvement predict the lowest productivity levels.

Overall, housing productivity differences across metros are large, with a standard deviation equal to 29 percent of total costs, with 30 percent of the variance explained by regulatory measures. Contrary to assumptions in the literature (e.g. Shapiro 2006 and Rappaport 2007) that productivity in tradeables and non-tradeables are the same, we find the two are negatively related, with productivity in housing decreasing, rather than increasing, in city size. Yet, we find, tentatively, that lower housing productivity due to land-use regulation is associated with a higher quality of life, albeit slightly less than is needed to compensate local residents for higher housing costs.

Our transaction-based measure of land values differs from other measures of land values that are based on the difference between an entire property's value and the estimated value of the structure built on its land. Davis and Palumbo (2007) employ this ”residual” method rather successfully, albeit "using several formulas, different sources of data, and a few assumptions about unobserved quantities, none of which is likely to be exactly right." Moreover, this method fails to capture how geographic and regulatory constraints increase the cost of producing housing, as these costs are attributed to the value of land. From our analysis, this may explain why Davis and Palumbo find the average cost-share of land in housing to be as high as 50 percent.

Ihlanfeldt (2007) takes measures of assessed land values from tax rolls in 25 out of 67 Florida counties, and finds that land-use regulations are associated with higher housing prices but lower land values. Rose (1992) acquires data on land values and housing rents across 27 major cities in Japan for over 35 years, although he does not examine the relationship between housing costs and land values or regulations. Glaeser, Gyourko, and Saks (2005b) focus on multifamily buildings in Manhattan to estimate the costs of housing production, as the marginal cost of building an additional floor does not require land, obviating the need for land price data.[1]

The econometric approach used here differs in that we use a cost-function approach to housing, which uses land as in input. This approach is similar to that of Epple, Gordon, and Seig (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. While our cost-share estimate for Pittsburgh is similar at

[1] Older works 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).

18.4 percent, we also estimate cost shares for most U.S. metro areas, using indices that account for differences in construction costs and a much wider away of regulations.[2] The variation across, rather than within, cities allows to also identify the cost structure from variation in labor and construction costs across cities, and produces a point estimate for the elasticity of substitution somewhat below one, consistent with much of the older literature that uses within-city variation – see McDonald (1981) for a survey of this literature – as opposed to larger estimates from Thorsnes (1997).

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 for the New York metro area. Using data in the San Francisco Bay Area, Kok, Monkkonen, and Quigley (2010) relate land values to the topographical, demographic, and regulatory features of the site. Nichols, Oliner, and Mulhall (2010) construct a panel of land price indices for 23 metro areas from the mid-1990s through 2009 to examine how land values vary more across time than structures, much as our analysis finds the same is true across space.

2 Model of Land Values and Housing Production

Our estimation is based on a cost-function approach to housing production, within a system-of-cities model proposed by Roback (1980) and developed by Albouy (2009). The national economy contains many cities indexed by j, which produce and trade a numeraire traded good, x, and produce 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] Although hedonic methods can theoretically provide estimates of land values, these estimates can be highly unreliable. For instance, Glaeser and Ward (2009) estimate a value of $16,000 per acre of land in the Greater Boston area using hedonic methods while presenting evidence that the market price of an acre of land is approximately $300,000 if new housing can be built on it, a discrepancy they attribute to zoning regulations.

2.1 Two-Input Model of Housing Production

We begin with a two-factor model in which firms produce housing 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. A_j^Y may be fixed or determined endogenously by city-level characteristics. 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 construction costs, possibly an aggregate of local labor and tradeable goods. Unit cost in the housing sector is $c^Y(r_j, v_j; A_j^Y) \equiv \min_{L,M}\{r_j L + v_j M : F_Y(L, M; A_j^Y) = 1\}$.

Assuming the housing market in city j is perfectly competitive[3], then in equilibrium housing price equals the unit cost in cities with positive production:

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

This equation is log-linearized around the national average to express how housing prices should vary with input prices and productivity.

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

where $\hat{z}^j$ represents, for any attribute z, city j's log deviation from the national average, $\bar{z}$, i.e. $\hat{z}^j = \ln z^j - \ln \overline{z} \cong (z^j - \overline{z})/\overline{z}$, ϕ^L is the average cost share of land in housing, and A_Y^j is normalized so that $\bar{A}^Y = -\bar{p}/[\partial c^Y(\bar{r}, \bar{m}, \bar{A}^Y)/\partial A]$, i.e. so that a one-point increase in $\hat{A}_j^Y$ corresponds to a

[3] Although this assumption may seem stringent, the empirical evidence is consistent with perfect competition in the construction sector. Considering evidence from the 1997 Economic Census, Glaeser et al. (2005b) report that "...all the available evidence suggests that the housing production industry is highly competitive." Basu et al. (2006) calculate returns to scale in the construction industry (average cost divided by marginal cost) as 1.00, which is indicative of firms in the construction industry having no market power.

one-point reduction in the in log costs. Rearranged, this equation measures unobserved local home-productivity from how high land and material costs are relative to housing costs:

$$\hat{A}_Y^j = \phi^L \hat{r}_j + (1-\phi^L)\hat{v}_j - \hat{p}_j \tag{4}$$

In other words, cities are inferred to have low housing productivity if the price of housing is high relative to local input costs.

If housing productivity is factor neutral, i.e., $F^Y(L, M; A_j^Y) = A_j^Y F^Y(L, M; 1)$, then the second-order log-linear approximation of (3) is

$$\hat{p}_j = \phi^L \hat{r}_j + (1-\phi^L)\hat{v}_j + \frac{1}{2}\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{v}_j)^2 - \hat{A}_j^Y \tag{5}$$

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

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

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

On the other hand, if housing productivity is not factor neutral, then equation (5) will contain an additional term to account for the relative 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 A_j^{YL}/A_j^{YM} is higher.[4]

[4] Appendix A contains greater detail on the model with factor-specific productivity.

2.2 Empirical 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:

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

Z^j is a vector of city-level 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

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

where $\phi^L = \beta_1$and, with factor-neutral productivity, $\sigma^Y = 1 - 2\beta_3 / \left[\beta_1(1-\beta_1)\right]$, and where housing productivity is determined by observable attributes in Z^j and unobservable attributes in the residual:

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

The functional form of the cost function resulting from the second-order approximation (i.e. the translog cost function) is not a constant-elasticity form. Therefore, the elasticities of substitution we estimate are evaluated at the sample mean parameter values (see Griliches and Ringstad 1971 p. 10 for a discussion). The assumption of Cobb-Douglas 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 cause 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:

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

where $\gamma_2 Z^j/2\beta_3 = (\hat{A}_j^{YM} - \hat{A}_j^{YL}) - (\hat{A}_{0j}^{YM} - \hat{A}_{0j}^{YL})$, identifies observable differences in factor-biased technical differences. If $\sigma_Y < 1$, then, $\gamma_2 > 0$ implies that the shifter Z lowers the productivity of land relative to the non-land input.[5]

2.3 Full Determination of Land Values

Land values and local-wage levels are determined using a model of location demand based on amenities to individuals, bundled in terms of quality of life, Q_j, and to firms in the tradeable sector, bundled as trade productivity, A_j^X.We posit two types of mobile workers, $k = X, Y$, where type-Y workers labor in the housing sector. Preferences are modeled by the utility function $U^k(x, y; Q_j^k)$, which is quasi-concave over x and y, increasing in Q_j^k, and summarizes the value of city j's amenities to k-types. The expenditure function for an individual is $e^k(p, u; Q) \equiv \min_{x,y}\{x + py : U^k(x, y; Q) \geq u\}$. Each individual supplies a single unit of labor and is paid $w_{j,}^k$, which together with with non-labor income, I, makes up total income m_j^k, out of which federal taxes $\tau(m_j^k)$ are paid. Assume that individuals are fully mobile and that both types occupy each city. Then equilibrium requires that individuals everywhere receive the same utility across all cities, so that higher prices or lower quality-of-life must be compensated with greater after-tax income:

$$e(p_j, \bar{u}; Q^j) = m^j - \tau(m^j) \tag{11}$$

where $\bar{u}^k$ is the level of utility attained nationally by individuals k. Log-linearizing this condition around the national average

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

[5]Note that now $\beta_1 = \phi_L + \beta_3 \left(\hat{A}_{0j}^{YM} - \hat{A}_{0j}^{YL}\right)$ and $\varepsilon^j = -\left[\phi^L \hat{A}_j^{YL} + (1 - \phi^L)\hat{A}_j^{YM}\right] + \frac{1}{2}\phi^L(1 - \phi^L)(1 - \sigma^Y)(\hat{A}_j^{YL} - \hat{A}_j^{YM})^2$

where Q_j^k is normalized so that $\bar{Q}^k = 1/[\partial e^k(\bar{p}, \bar{u}^k, \bar{Q}^k)/\partial Q]$, s_y^k is the average expenditure share on housing, and τ^k is the average marginal tax rate for type k, and s_w 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^X is the share of income earned by workers in the tradeable sector, and let $s_y \equiv \mu^X s_y^X + \mu^Y s_y^Y$, and $(1-\tau)\, s_w \hat{w} \equiv \mu^X (1-\tau^X) s_w^X \hat{w}_j^X + \mu^Y (1-\tau^Y) s_w^Y \hat{w}_j^Y$.

The productivity of firms in the tradeable sector is modeled as in the housing sector except that output has a uniform price across cities and is produced through the CRS and CD function, $X_j = F^X(L, N^X, K; A_j^X)$, where N^X is labor and K is mobile capital, which also has the uniform price, i, everywhere. A derivation similar to the one for (3) 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. Note that land is paid the same price in both sectors. To complete the model, let non-land inputs be produced through the CRS and CD function $M_j = F^M(N^Y, K)$, which implies $\hat{v}_j = \varpi^N \hat{w}_j$, where ϖ^N is the cost-share of labor. Defining $\phi^N = \varpi^L(1-\phi^L)$, we have

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

Combining the productivity in both sectors, define the total productivity differential as

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

where s_x is the average expenditure share on tradeables.

Combining equations (12), (13), (14), and (15) in the case where $\sigma^Y = 1$, we get that the land-value differential, times the 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 a tax differential to the federal government that depends on wages:

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

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

Proper identification of the model requires that these determinants of land values are uncorrelated with unobserved determinants of A_Y in the residual. To some extent, this is inevitable if the vector of housing productivity characteristics Z^j is incomplete and $\hat{A}^j_{Y0} \neq 0$. We could try to account for the simultaneous determination of $\hat{r}^j$ by $\hat{A}^j_{Y0}$, but this would still require making assumptions about the covariance structure between $\hat{A}^j_X$,$\hat{A}^j_Y$, and $\hat{Q}^j$. A more plausible strategy may be to find instrumental variables that influence $\hat{A}_j^X$ or $\hat{Q}^j$ but are unrelated to $\hat{A}_j^Y$, however, even those may be very difficult to find. In Appendix E we consider using average winter temperatures as an instrument and find results statistically consistent with the ordinary least squares estimates below.

3 Data

We calculate our land price index from the CoStar COMPS database of commercial real estate sales. 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 the term "land." In this study, we take as our initial data set every commercial land sale in the COMPS database provided by CoStar University, which is provided for free to any academic researcher, through the end of 2010.[6] We restrict our data set to transactions that occurred between 2005 and 2010 in a metropolitan area, and exclude all transactions CoStar has marked as non-arms length. We also exclude transactions that appear to feature

[6]We downloaded data from March through June 2011.

a structure, as evidenced by the inclusion of a field in the transaction record for “Bldg Type”, “Year Built”, “Age”, or the phrase “Business Value Included” in the field “Sale Conditions”. After dropping observations without complete information for lot size, sales price, county, and date, we are left with 73,166 observations.[7] Next, we drop observations we could not geocode successfully and those geocoded at the region level of accuracy or worse, using the Stata module “geocode” described in Ozimek and Miles (2011)[8]. We are left with 68,757 observed land sales.

Summary statistics for our sample of land sales are shown in Table A2. We observe land sales in 324 Metropolitan Statistical Areas and Primary Metropolitan Statistical Areas.[9] The median price per acre in our sample was $272,838, while the mean was $1,536,374; the median lot size was 3.5 acres while the mean was 26.4. CoStar provides a field describing the “proposed use” of each property; properties can have multiple proposed uses or none at all. We use 12 of the most common categories of “proposed use” which are neither mutually exclusive nor collectively exhaustive, as well as an indicator for no proposed use, in our analysis of land values. Approximately 15.9% of the properties sold in our sample had no proposed use listed, while five categories of proposed use, ‘Retail’, ‘Industrial’, ‘Single Family’, ‘Office’, and ‘Hold for Development’, each comprised more than 5% of our sample.

We calculate a land-value index by city for each year by regressing the log price per acre of each sale on a set of dummy variables for each MSA or PMSA and a set of dummies for quarter of sale. In successive specifications, we add log lot size, followed by a set of dummies for planned use. A major concern with this approach is that the land sales we observe are not a random sample of all land parcels. In our preferred specification, we use a geography-based weighting scheme to mitigate potential selection bias, overweighting parcels where residential housing is dense and underweighting parcels where it is scarce. We take the regression coefficient on each MSA or PMSA dummy to be our index of land price differentials for each city. Some results of the

[7] We also exclude outlier observations with a listed price of less than $100 per acre or a lot size over 5,000 acres.

[8] Again, 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 method described in section 4.1, Land Values.

[9] We use the June 30, 1999 definitions provided by the Office of Management and Budget.

land value regressions, shown in Table 1, along with further details of our geographical weighting scheme, are discussed in section 4.1.

We calculate wage and house price differentials for each year from the 2005-2010 American Community Survey. Our method, described in detail in the Appendix, involves regressing wages and housing costs on a rich set of observable characteristics, including a set of indicators for each metro area. The coefficients on these metro indicators provide our indices of wages and housing costs. Wages are estimated separately for workers in the construction industry; as seen in Appendix Figure B, they are generally similar to but more dispersed than overall wages.

In certain sepcifications we use an estimate of housing costs based on a combination of rents and imputed rents so as to have a fully representative sample of the housing stock in a given area. As seen in Appendix Figure C, housing prices are considerably more dispersed than rents.

To measure the regulatory and geographic environments of metropolitan areas, we use the Wharton Residential Land Use Regulatory Index (WRLURI), described in Gyourko, Saiz (2008). The index is based on survey responses from municipal planning officials regarding the regulatory process to create 11 subindices, constructed so that higher scores corresponds 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 WRLURI is constructed by factor analysis.[10] The components of the WRLURI generally have positive correlations with one another but not always; for instance, the SCII is negatively correlated with five of the other subindices.

The index of topographic constraints to residential development is developed 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

[10]Two of the subindices measure state-level behavior, while nine are sub-state/local. The LAI measures whether zoning requests must be approved at a town meeting, a feature unique to New England; all other subindices are national in scope.

if it is covered by water or wetlands, or has a slope of 15 degrees or steeper, which effectively inhibits development. While this land is not actually built on, it serves as a proxy for geographic features that may lower housing productivity. In somre specifications we also use a measure of the mean slope in a metropolitan area based on our own calculations. We re-normalize both the WRLURI and Saiz indices to be $z-$scores, with a mean of zero and standard deviation one, as weighted by population in our sample[11].

Construction costs are measured using the Building Construction Cost data from the RS Means company, which is widely used in the literature, e.g. Davis and Palumbo (2007), Glaeser, Gyourko and Saks (2005b). For each city in their sample, RS Means reports construction costs for a composite of nine common structure types, which we report proportional to the national average, normalized to 100. The index includes the costs of labor, materials, and equipment rental, but not cost variations from regulatory restrictions, restrictive union practices, or regional differences in building codes.[12]

We restrict our analysis to metropolitan areas with at least 20 land-sale observations with at least 10 in a given year, that have available WRLURI, Saiz and construction wage indices, leaving 171 MSAs and 688 MSA-year combinations[13]. These use 68,757 land sale observations, 7.5 million wage observations – 339,524 of which are in the construction sector – and 4.1 million housing-cost observations. To interpret our results, we re-normalize our housing price, wage, and construction wage differentials, as well as the RS Means index, to have a population-weighted mean of zero within this sample. Because these variables are calculated as log deviations from this average, the re-normalized variables can be interpreted as the log deviation from the national average.

We also re-normalize our measures of geographic and regulatory constraints, including their

[11] As Saiz (2010) does, we find that his index of topographic constraints is positively correlated with the WRLURI, with a correlation coefficient of 0.302 (s.e. = 0.102).

[12] 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.

[13] of these, 165 are included in the RS Means construction cost index

individual components, to have a population-weighted mean of zero within the sample. These re-normalized variables are interpreted as standard deviations from the national average.

4 Results

Below we present results of the model accounting in sequence for non CD-production, geographic and regulatory constraints, non-land input costs, and disaggregated measures of regulatory and geographic constraints. In the appendix, we take a brief look at the reverse regression of land values on housing costs and other variables, and briefly consider the stability and potential endogeneity of our results.

4.1 Land Value Index

We report the results of our land value regressions in Table 1[14]. Proceeding from our estimates with few controls to our preferred estimates, we start by regressing log price per acre on a set of MSA dummies with no additional controls. The R^2 of this regression is 0.28, but the results are similar to those in our preferred specification, column 4. The correlation coefficient of these two measures in the sample is 0.88 when weighted by the number of observed land sales, although the differentials in specification 1 are more variable. In column 2, we add the log lot size in acres. Controlling for lot size improves the R^2 substantially to 0.68. The coefficient on lot size is -0.65, which implies that when parcel size doubles, the total price of the parcel rises only 42 percent: this is the "plattage effect," first reported by Colwell and Sirmans (1980).[15] The logic used to explain this effect is that 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 parts of the metropolitan area.

In specification 3, we add controls for quarter of sale and a number of intended-use categories.

[14]Currently, Table 1 reports results from regressions pooled at the MSA level.
[15]For a summary of subsequent documentation, see Colwell and Sirmans (1993).

The R^2 of the regression rises modestly but the land value differentials change little; the weighted correlation between the land value differentials in specifications 2 and 3 is 0.995.

One concern with our estimation strategy for the land value differentials is selection bias, as the sample of lots in our dataset is not a random sample of all lots. As discussed in Nichols et al. (2010), it is impossible to correct for possible selection bias because we do not observe lots that are not sold[16]. One especially relevant source of selection bias in our sample is that the geographic distribution of observed land sales may differ systematically from the distribution of land throughout the metro area. For instance, we may be more likely to observe land sales on the urban fringe, where development activity is more intense.

In column 4, we control for the geographical distribution of the land sales we observe by re-weighting our observations to reflect the distribution of housing units throughout the city. For each MSA or PMSA, we regress the log number of housing units per square mile at the census tract level on the North-South distance between the tract center and the city center, the East-West distance between the tract center and city center, the squares of these differences, and the product of the differences. We use the Google Maps definition of city centers, generally within a few blocks of city hall. We then define the predicted density of each observed land sales using the city-specific coefficients from this regression applied to the same set of distance controls for the individual properties. The weighted correlation between the land rent differentials in specifications 3 and 4 is high at 0.96, but the differentials with the geographic weighting are more dispersed, with a standard deviation of 0.698 versus 0.619 for the differentials without the geographic weighting. Weighting by predicted density increases the R^2 of the regression from 0.70 to 0.76. Figure 1 illustrates the weighted and unweighted land rent differentials for each MSA and PMSA. Table A3 reports the land rent differentials for each specification.

We take the fourth set of land value differentials in Table A3, corresponding to column 4 of Table 1, as our preferred estimates. The highest land values in the sample are in New York and San

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

Francisco. In general, large, coastal cities have the highest land values, while smaller cities in the South and Midwest have lower values. The lowest values are in the Midwest, with Youngstown, Ohio and Evansville, Indiana having the lowest land values in our sample.

4.2 Simple Model with Constraints

The land-value and housing-cost indices are plotted against each other in figure 2A. A simple linear regression produces a slope of 0.56, which, assuming all other costs are uniform across cities, is land's estimated share of costs assuming CD production. The flexible curvature in the quadratic regression yields an estimate of the elasticity of substitution of 0.58, which implies a wide range of cost shares across metro areas from 19 to 88 percent, although it is imprecisely estimated. Visually, a city's housing productivity is given by the vertical distance below the regression line: thus, San Francisco has low housing productivity and Las Vegas has high housing productivity. The curves here represent estimates from the data with no controls, and change as other variables are added to the model.

Our methodology of estimating housing productivity is illustrated in figure 2B. 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.

By assuming that the national economy may be represented with a single elasticity of substitution, we may confound cities that have low substitutability for cities that have low productivity. When cities have low substitutability, the cost curve is flatter, as shown by the dashed line, as housing producers do not use less land in higher-value cities. This has the same observable consequence of increasing housing prices, although theoretically the concepts are different. The supply of housing, measured as a quantity, is less responsive to price increases when substitutability is low than when productivity is low.

The results in columns 1 and 2 of table 3 include the basic geographic and regulatory measures. This reduces the estimated cost-share of land, and the estimated elasticity of substitution also declines to 0.45, statistically lower than one. Moreover, a standard deviation increase in either the geographic constraint or regulatory index predicts a 12 to 13 percent increase in housing costs, respectively, effects that are consistent with theory.

Column 3 presents results using a housing-cost measure based only on gross rents; the lower estimates suggest that rents are less responsive to differences in land values and constraints. Column 4 presents results using a measure of housing costs derived from a combination of gross rents and imputed rents; the estimated land share is between the values derived from owner-occuied units and rental units individually.[17]

Overall, the results of these simple regressions are encouraging: the estimated cost share of land and the elasticity of substitution between land and other inputs into housing production are quite plausible, while the coefficients on the regulatory and geographic constraints have the predicted sign and reasonable magnitudes. The surprisingly good fit, as measured by R^2, of these basic specifications suggests that land rents and the geographic and regulatory constraints drive a substantial amount of the variation in housing costs across metro areas. The plausibility of these results suggests that ommitted variable bias in our regressions may be less of a concern than one might suppose.

4.3 Non-Land Input Cost Differences

Construction costs and wages are plotted against land values in figures 3A and 3B: both of these measures of non-land input costs are strongly correlated with land values. This means that estimates of ϕ_L without these costs are biased positively.[18] The figures also plot estimated zero-profit

[17] Figure C plots housing values against housing rents and shows that the two are strongly correlated, although a one-percent increase in rents predicts a 1.87-percent increase in housing values, or a 1.67-percent increase in the combined housing-cost measure.

[18] These measures are strongly correlated, as shown in Appendix Figure A, although there are some considerable deviations, especially in New York, where costs are high relative to wages, while the opposite is true in Las Vegas.

conditions (ZPCs) for firms, derived from equation 5 estimated without controls. These correspond to fixed values of housing costs and productivity, $\hat{p}_j + \hat{A}_j^Y$. With the log-linearization, the slope of the ZPC is the ratio of land costs to non-land costs, $-\phi_j^L/(1-\phi_j^L)$, which in the CD case is constant. With an estimated elasticity, σ^Y, of less than one, the slope of the ZPC increases with land values, as the land-cost share is rising with land prices. Firms in cities with higher productivity or higher housing costs pay their inputs higher prices, and have ZPC's further to the right.

To visualize the relationship between productivity and housing costs, consider the three-dimensional surface shown in figure 3C, which predicts housing costs from land values and construction costs using the estimated cost function. Cities with housing costs above this surface are identified with lower housing productivity than cities below it.

As seen already in the figures, accounting for non-land costs lowers the implied cost-share of land. Table 4A presents estimates using the RS Means construction costs: columns 1 and 2 use the linear-CD specification, while columns 3 and 4 use the translog specification; columns 2 and 4 impose the CRS restrictions, which reassuringly pass at the usual statistical sizes. This means that, conditional on productivity, housing exhibits constant returns at the firm level. The point estimate of σ^Y implied by the estimates in column 4 is 0.53 and the Cobb-Douglas restrictions are not rejected at the 10% confidence level, implying that the CD specification is not wholly unreasonable. In this specification, we find a cost-share of land of 28 percent and a somewhat smaller impact of regulatory constraints, wich are positively correlated with construction costs.

In column 5 we check for the possibility that productivity in the housing sector is non-neutral, meaning it augments one factor more than another. To test this, we estimate the interaction between observable shifters of productivity, i.e. the geographic and regulatory constraints, with land values minus construction costs. Both interactions are statistically insignificant, and thus we are unable to detect factor-specific productivity differences.

In column 6, we estimate the specification from column 4, but calibrate the cost share of land to 0.4 and the construction cost share to 0.6. The estimated elasticity of substitution is essen-

Construction wage levels are also strongly tied to local wage levels, but not perfectly.

tially unchanged, while the estimated impacts of the geographic and regulatory constraints decline slightly.

Results in columns 1 through 4 of table 4B, which use construction wages, rather than costs, are similar. The point estimate for σ^Y is 0.50, statistically less than one, so that the CD specification is rejected at the 5% level. The estimates in column 5 imply that a 1-percent increase in construction wages predicts a 0.55 percent increase in construction costs, which appear unrelated to land costs, geographic constraints, and the regulatory index. In column 6, we report estimates allowing for a third factor, capital, which is unobserved and has constant costs across areas. We constrain its cost share to be the remainder not accounted for by land or the fraction of construction costs predicted by constructions costs, approximately 40 percent. In column 7, we again allow for non-neutral productivity differences, but do not find any significant evidence for them. These specifications produce similar estimates for the land cost share and impacts of geographic and regulatory constraints.

In columns 8 and 9, we again present results using calibrated cost shares. In column 8, we set the cost share of land to 0.4 and the cost share of construction wages to 0.6, while in column 9 we set the cost share of land to 0.4, the cost share of construction wages to 0.27, and the cost share of mobile capital to 0.33, using the same procedure as in column 6. The elasticity of substitution is estimated to be higher in column 8 than in column 4, but not significantly so, while the effects of the geographic and regulatory constraints are estimated to be somewhat lower in columns 8 and 9. Overall, we conclude from the calibrated models that the estimates of the non-cost share parameters are not highly sensitive to the estimated cost shares.

4.4 Disaggregating the Regulatory and Geographic Indices

As discussed above, the WRLURI regulatory index used in the analysis is an aggregation of 11 subindices. The factor loading of each subindex is reported in Table 5, ordered according to the size of its factor load. Alongside, in column 1, are estimates from a regression of the WRLURI z-score on the z-scores for all of it component subindices. The coefficients vary from the factor loading coefficients because the sample and weighting differ from those used in the original construction of the WRLURI.

In column 2, we examine disaggregated versions of the geographic constraint index, kindly provided to us by Albert Saiz. Specifically, we break the geographic index into two parts, the flat land share and the solid land share. The negative coefficients on the constituent parts are expected because the geographic constraint index measures the share of land that is unavailable for development, while these measures indicate the fraction of land suitable for development.

In columns 3 and 4 we report results using the CRS specifications from column 4 of tables 4A and 4B, but with the disaggregated regulatory and geographic subindices. The results are intriguing as the subindices vary widely in terms of their estimated effects on housing costs. However, the three subindices with the higest factor loadings, approval delays, local political pressure, and state political involvement, are all associated with high housing costs, as is state court involvement. None of the subindicies appears to lower costs at a statistically significant level in any of the specifications. We find that higher flat land and solid land shares lower costs, as expected. We find that the cost-share of land appears to be between 22 and 23 percent and that the elasticity of substitution is between 0.62 and 0.65, significantly lower than one. In the remainder of the paper, we take the results in column 3 of table 5 as our preferred estimates. These results predict the cost share of land in the sample ranges between 10 and 35 percent.

4.5 Productivity in Housing and Tradeables

In table 6 we provide measures of housing productivity from the empirical model in column 6 of table 5, where $\hat{A}_j^Y = Z_j(-\gamma^*) - \varepsilon_j^*$, where the $*$ refers to estimates. Using our indices of land values, housing costs, and overall wages, and calibrating values for the other parameters in the model, we also provide estimates for tradeable productivity $\hat{A}_j^X$ and overall quality-of-life $\hat{Q}_j$.[19] The two productivity measures are plotted against each other in Figure 4, which displays iso-productivity

[19]This calibration, explained in Albouy (2009), is $s_w = 0.75$, $\tau = 0.33$, $s_y = 0.22$, $s_x = 0.64$, $\theta^L = 0.025$, $\theta^N = 0.8$. A few details still need to be explained.

lines for cities with same level of productivity when housing and tradeables are weighted by their expenditure shares. The cities with the most productive housing sectors are McAllen-Edinburg-Mission, TX and Springfield, MO; Among metros with over one million inhabitants, the top five are Pittsburgh, Buffalo, Indianaplois, Rochester, and Houston. The least productive metros are typically along the coasts, with Santa Rosa, CA, at the bottom of the list, followed by San Francisco and Ventura, CA, .[20]

The most productive cities with over one million inhabitants in the United States overall are New York, which has high tradeable productivity and only slightly below average housing productivity, Philadelphia, which has above average productivity in both sectors, and Houston, which has average tradeable productivity and very high housing productivity. In tradeables alone, the most productive places are in the Bay Area, San Francisco and San Jose. Also shown is a line which depicts the bias to tradeable 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 tradeable productivities, as cities with higher housing productivity have housing values low relative to land values, leading to lower inferred measures of tradeable productivity. In this case, cities in the Bay Area would have their land costs and tradeable productivities over-stated.

Rather than the two productivity types matching one-for-one, the two are negatively related, with a 1-percent increase in trade-productivity predicting a 2.3-percent decrease in housing productivity. While cities may exhibit increasing returns to scale at the city level in the tradeable sector, there could be decreasing returns to scale in the housing sector; i.e., agglomeration economies in tradeables are offset by agglomeration diseconomies in non-tradeables. We explore this hypothesis in table 7, which examines the relationship of productivity with population levels, at the consolidated metropolitan (CMSA) level, in panel A, or density, in panel B. The negative relationship between housing productivity and either metro population or density in column 2 is large, significant, and larger than the positive relationships with trade productivity in column 1. Much of

[20] These productivities are positively related to the housing supply elasticities, with a 1-point increase in productivity predicting a 1.94-point (s.e. = 0.24) increase in the supply elasticity ($R^2 = 0.41$).

this appears to be the result of endogenous regulatory behavior increasing in larger, denser cities: the relationship is much weaker in column 3, which excludes the component of housing productivity due to the regulatory subindices. The overall agglomeration economies measured through total productivity in column 4 are significantly smaller than the economies measured through trade productivity alone in column 1.

4.6 Housing Productivity and Quality of Life

The analysis above suggests that the overall productivity of larger cities is hampered by regulatory burdens that lower the welfare of individuals by inflating their housing costs. Yet, the close proximity of urban life is thought to create negative externalities, which if left uncontrolled, can lower the quality of life in cities. This raises the possible utility of regulations, especially with regards to housing, which can mitigate the impact of these externalities, such as through "externality zoning."

Figure 5 shows a striking negative relationship between housing productivity and quality of life measurements. This relationship must be regarded cautiously, not only because of usual endogeneity issues, but because both measures are derived from housing costs: higher costs signal greater quality of life and lower productivity, which can induce an unwarranted mechanical relationship between the two variables. Results in table 8 temper some of these issues by controlling for possible confounding factors, with column 1 adding variables for natural amenities such as climate and adjacency to the coast, as well as the geographic constraint index; column 2 adds artificial amenities such the population level, density, education levels, crime rates and number of eating and drinking establishments. These natural controls effectively serve to reduce the relationship by roughly a half, although the artificial controls do little more. To better understand the role of regulation and to help purge the estimates of their mechanical correlation, columns 3 and 4 use only the portion of housing productivity predicted by the regulatory subindices. The results using this measure are of roughly the same magnitude, which lends some credibility to the hypothesis that regulations in the housing sector improve the welfare of local residents.

A cursory analysis based on equations (15) and (16) suggests that if the elasticity of quality of life with respect to housing productivity is greater in absolute value than the expenditure share on housing, then these regulations may actually increase the overall value of land, and could be welfare improving. In fact the coefficient estimates in table 8 are smaller at 4 to 6 percent.

Other explanations for this phenomenon are equally plausible. For instance individuals in nicer areas may endogenously choose regulations to restrict in-migration. 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, which can raise the willingness-to-pay of the marginal resident, much as in the "Superstar City" hypothesis of Gyourko, Mayer, and Sinai (2006).

5 Conclusion

The best empirical model from this analysis suggest that the average share of land in housing costs in metropolitan areas is slightly less than 22 percent. Without controls for building costs and geographic and regulatory constraints, this share may be overestimated. The elasticity of substitution between land and other factors is about 0.6, so this share varies widely across metro ares from 0.10 to 0.35. Since residential housing constitutes roughly 22 percent of gross household expenditures, these results suggest that income from land constitutes a fairly large portion of national income accounts, with residential land accounting for 4.5 percent of income.

Housing productivity varies considerably across metro areas with a standard deviation of 0.25 of total costs, with coastal and larger urban areas having the least efficient housing sectors. Both geographic and regulatory constraints play a strong role in lowering productivity. Among regulatory constraints, approval delays, local politial pressure, and state political involvement appear to have the greatest role in raising costs.

Overall, diseconomies in housing productivity appear to offset some of the gains associated with agglomeration, as measured through productivity in tradeables and seen largely in higher wage levels. Our estimates suggest that this effect could be diminished if regulations were relaxed but that doing so could have negative consequences for the quality of life of local residents. Additional research is needed to control for the possible endogenous responses of regulation, and to better determine the causal relationships between the many factors associated with land values and the overall welfare of the population.

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Appendix

A Factor-Specific Productivity Differences

If housing productivity is factor specific, i.e., $F^Y(L, M; A_j^Y) = F^Y(A_j^{YL}L, A_j^{YM}M; 1)$, then the cost function log-linearized around the national average gives

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

making it difficult to identify separately. The second-order log-linear approximation of 3 is

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

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

$$+ \phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{v}_j)(\hat{A}_j^{YM} - \hat{A}_j^{YL}) \tag{A.4}$$

$$- \left[\phi^L \hat{A}_j^{YL} + (1-\phi^L)\hat{A}_j^{YM}\right] + \frac{1}{2}\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{A}_j^{YL} - \hat{A}_j^{YM})^2 \tag{A.5}$$

The additional terms on the second-to-last line show 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. The following reduced-form equation

$$\hat{p}_j = \beta_1 \hat{r}_j + \beta_2 \hat{v}_j + \beta_3(\hat{r}_j)^2 + \beta_4(\hat{v}_j)^2 + \beta_5(\hat{r}_j\hat{v}_j) + \gamma_1 Z^j + \gamma_2 Z^j \hat{r}_j + \gamma_3 Z^j \hat{v}_j + \varepsilon_j \tag{A.6}$$

may be used to identify these effects, with the restriction that $\gamma_2 = -\gamma_3$.

B Reverse Regression

An alternate way to estimate the parameters of this model is to run the reverse regression of land values on housing costs and the other regressors. In the CD case

$$\hat{r}_j = \frac{1}{\phi_L}\hat{p}_j - \frac{1-\phi_L}{\phi_L}\hat{v}_j + \frac{1}{\phi_L}\hat{A}_j$$

The results of this regression, shown in table A4, suggest a larger share of land costs relative to non-land costs.

C Estimate Stability

We conduct two exercises in order to guage the stability of the estimates we present. First, we split the sample into three subsamples for 2007, 2008, and 2009. In table A5, soon to be available, we report the results for the regressions from table 4A, column 4 and table 4B, column 4, using the yearly samples and the pooled set of yearly samples. The replicated regressions are the translog regressions restricted to have CRS and using construction costs and construction wages, respectively as measures of non-land input costs. The average cost share of land ranges from 15.6 percent to 25 percent, while the estimated elasticity of substitution ranges from 0.29 to 0.79. The coefficients on the geographical and regulatory constraint indices are fairly constant across samples and are close to those estimated in the full sample.

Second, we report results for the same regressions using residential land rents only and "raw" land rent differentials. We define land as being residential if its intended use is listed as single family, multifamily, or apartments, and we calculate the raw land rent differentials by regressing log price per acre on a set of MSA dummies without any additional covariates. The estimated land cost share ranges from 24.7 percent to 31.3 percent, and the coefficients on the geographic and regulatory constraint indices are again quite similar to their values in the other specifications. The implied elasticity of substitution ranges from 0.32 to 1.09. We take these exercises as modest evidence in favor of the stability of our estimates, with the caveat that the estimated elasticity of substitution varies substantially across specifications.

D Wage and House Price Differentials

For the wage regressions, we include all workers who live in an MSA, 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, including:

- survey year dummies;
- age and age squared;
- 12 indicators of educational attainment;
- a quartic in potential experience and potential experience interacted with years of education;
- 9 indicators of industry at the one-digit level (1950 classification);
- 9 indicators of employment at the one-digit level (1950 classification);
- 5 indicators of marital status (married with spouse present, married with spouse absent, divorced, widowed, separated);
- an indicator for veteran status, and veteran status interacted with age;

- 5 indicators of minority status (Black, Hispanic, Asian, Native American, and other);
- an indicator of immigrant status, years since immigration, and immigrant status interacted with black, Hispanic, Asian, and other;
- 2 indicators for English proficiency (none or poor).

All covariates are interacted with gender.

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 differentials from the MSA indicator variables. 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.

House price differentials are also calculated using the 2006-2008 American Community Survey 3% sample. The differential housing price of an MSA is calculated in a manner similar to the differential wage, by regressing actual or imputed rent on a set of covariates. We impute a rent of 7.85% annually on the value of owner-occupied housing. We exclude utility payments from our measures of housing costs. 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).

Additionally, in one of our specifications we attempt to control for distance of the housing unit from the city center. For each 2000 Census PUMA, we calculate population-weighted centroids aggregated from the census tract level. We then measure the driving distance and driving time from these centroids to the city center using the Google Maps API. We use the first listed city in each

MSA or PMSA as our destination city, so, for instance, the destination associated with the Vallejo-Fairfield-Napa, CA PMSA would be Google Maps' definition of the center of Vallejo, CA. We successfully calculated driving distances and times for 1,672 of the 1,691 metropolitan PUMAs.

A regression of housing values on housing characteristics and MSA indicator variables is first run using only owner-occupied units, 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 for all units, rented and owner-occupied, on the housing characteristics fully interacted with tenure, along with the MSA indicators, which are not interacted. The house price differentials are taken from the MSA indicator variables in this second regression. 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.

E Endogeneity of Land Values

One potential challenge for our estimation strategy is the possibility that land values are endogenous. In our regression estimates of the housing production function, the error term has the structural interpretation of reflecting an MSA's productivity in the housing sector that is not accounted for by our geographic and regulatory controls. In the spatial equilibrium model we employ, land values, wages, and house prices are simultaneously determined in a system of equations as functions of quality of life, productivity in the tradeable sector, and productivity in the non-tradeable sector, which we interpret as the housing sector[21]. Therefore, land values may be correlated with productivity in the housing sector, violating the identifying assumptions of our OLS regressions.

We employ an instrumental variables approach to account for the potential endogeneity of land values. Because of the interpretation of the error term in our regressions as productivity in the housing sector, we wish to avoid potential instruments that might also affect productivity. Therefore, we focus on potential instruments that affect land values through quality of life and that we hope do not inluence productivity. The instrumental variable we choose to employ is average winter temperature. The amenity value of average January temperatures has been well-documented, for instance by Glaeser and Tobio (2008). We find that the average winter temperature is positively correlated with land values as well. To be a valid instrumental variable, average winter temperatures must also be uncorrelated with productivity in the housing sector, conditional on our geographic and regulatory controls, i.e. warm winter temperatures per se cannot increase productivity in the housing sector.

Table A7 displays the results of our instrumental variables regressions. Because we are unable

[21] The system of equations is

$$\begin{aligned} -s_w(1-\tau')\hat{w}^j + s_y\hat{p}^j &= \hat{Q}^j \\ \theta_L\hat{r}^j + \theta_N\hat{w}^j &= \hat{A}^j_X \\ \phi_L\hat{r}^j + \phi_N\hat{w}^j - \hat{p}^j &= \hat{A}^j_Y \end{aligned}$$

See Albouy (2009) equations 4a-4c for details.

to find a good instrument for the land value differential squared, we are limited to estimating only the Cobb-Douglas form of our housing production function equations. In column 1, we estimate the unrestricted version of the housing production function using the R.S. Means construction cost data, while in column 2 we restrict the cost shares to sum to one. In columns 3 and 4 we use wages in the construction sector in place of the construction cost data. The average winter temperature is a statistically significant predictor of land values in all of the specifications, and the first stage F-statistics are also very high. The cost share of land in housing is higher in the instrumental variables regressions than in the OLS regressions. However, these differences do not appear to be statistically significant: in no case does a Chi-squared test reject the null hypothesis that the land value differential can be treated as exogenous at the 5% confidence level. We therefore take the instrumental variables estimates as evidence that our baseline specifications may understate the cost share of land in housing slightly, but that the difference does not appear to be statistically significant.

Figure 1: Weighted vs. Unweighted Land Rents

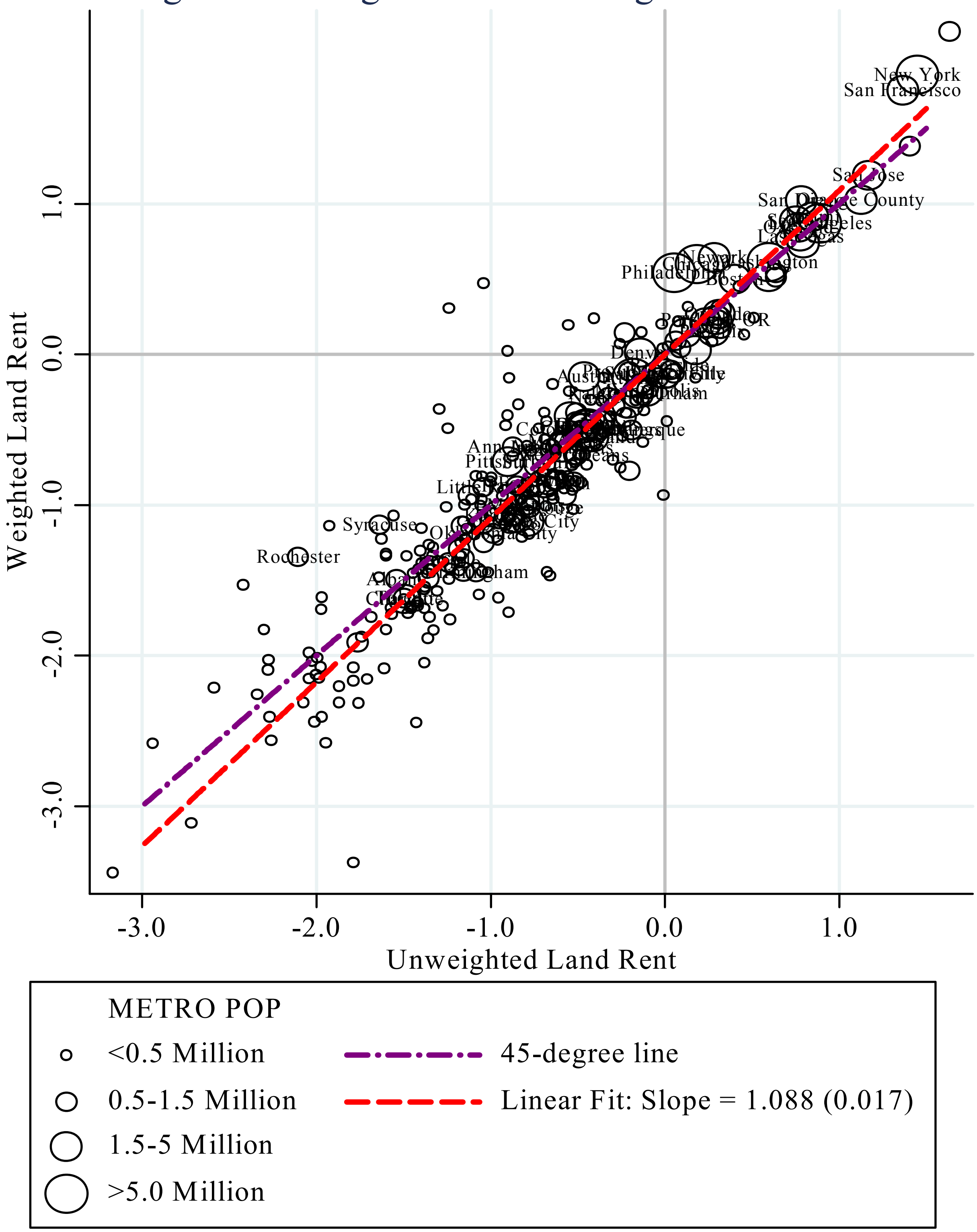
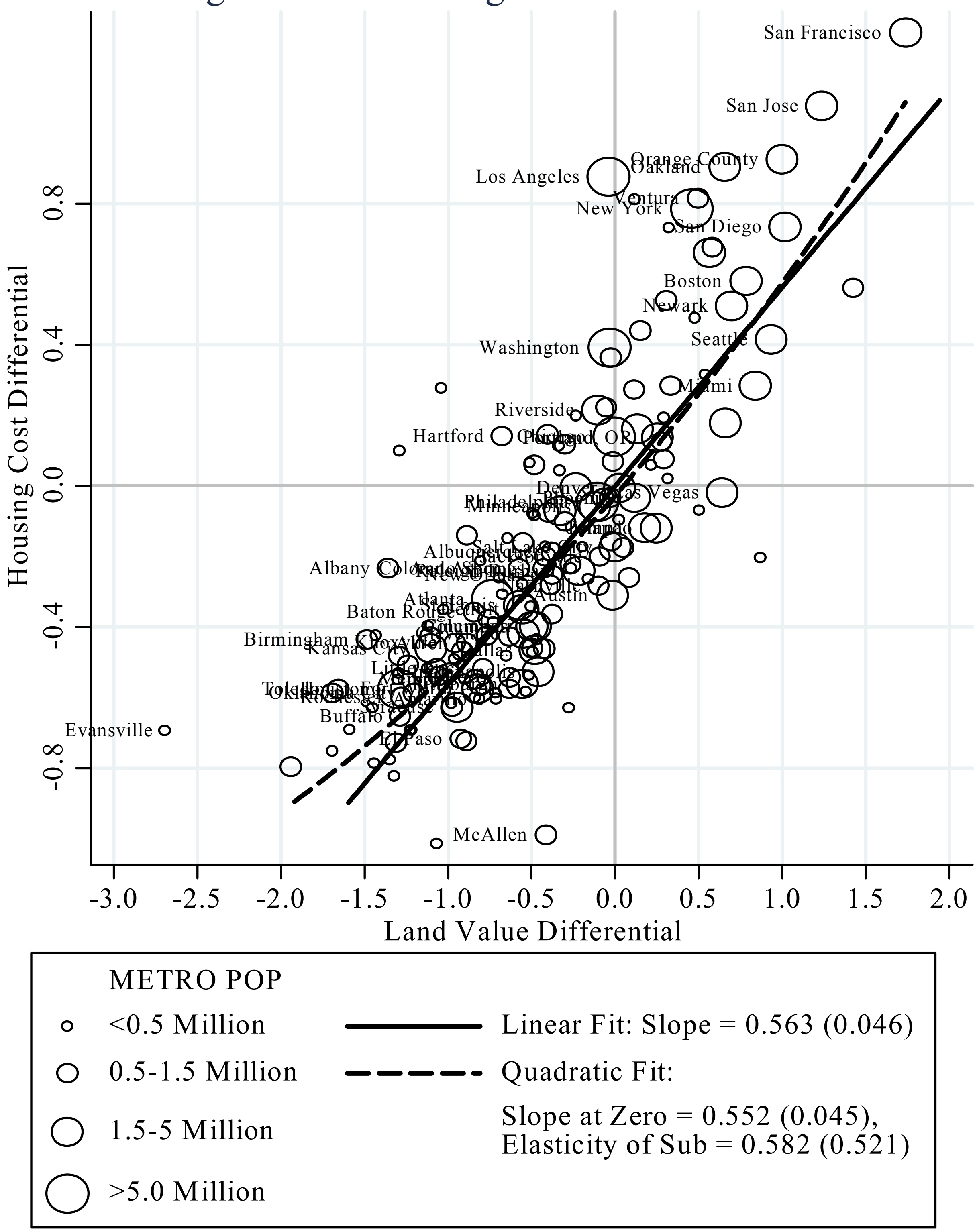


Figure 2A: Housing Costs vs. Land Values



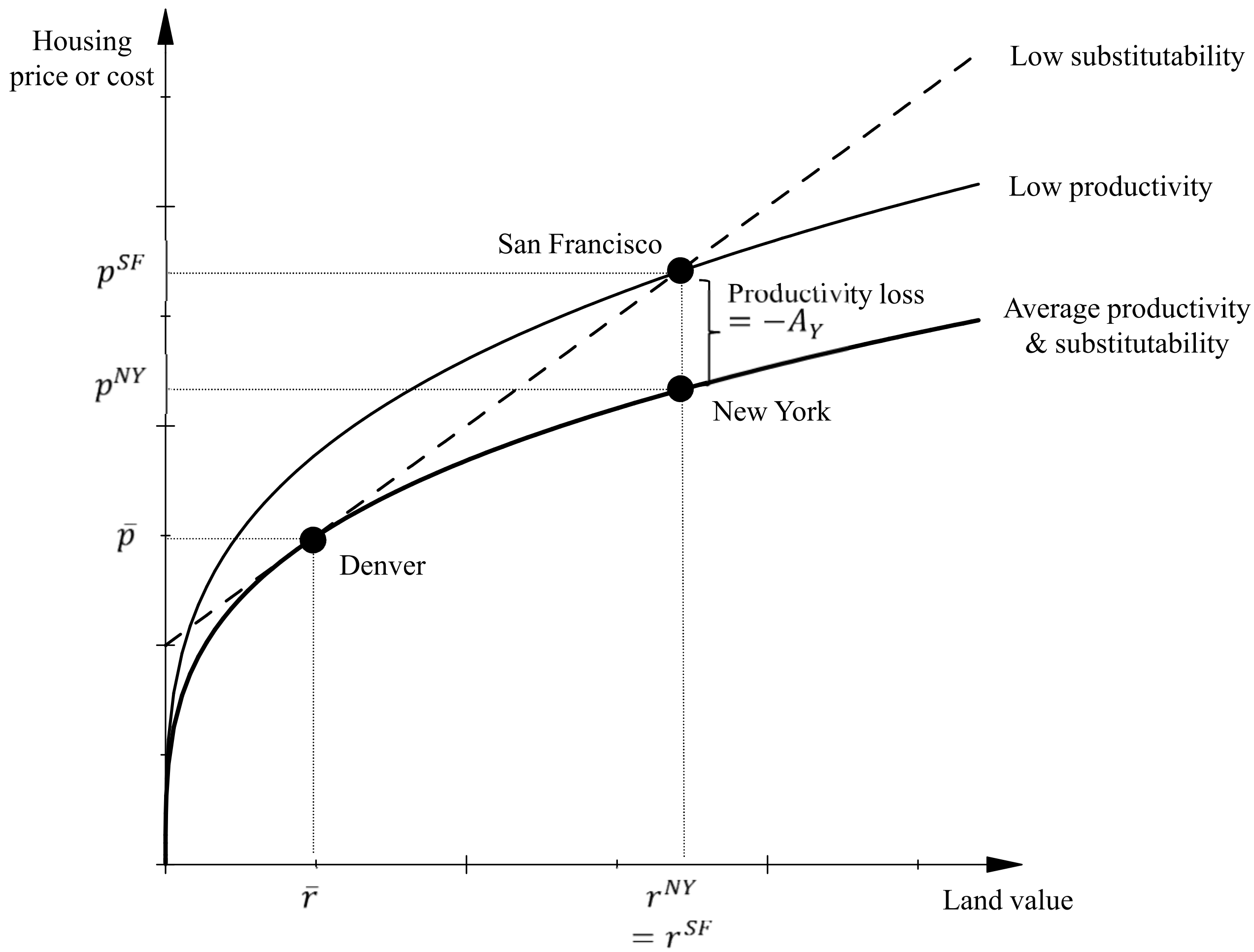


Figure 2B: The effect of low productivity or low substitutability on housing prices

Figure 3A: Construction Costs vs. Land Values

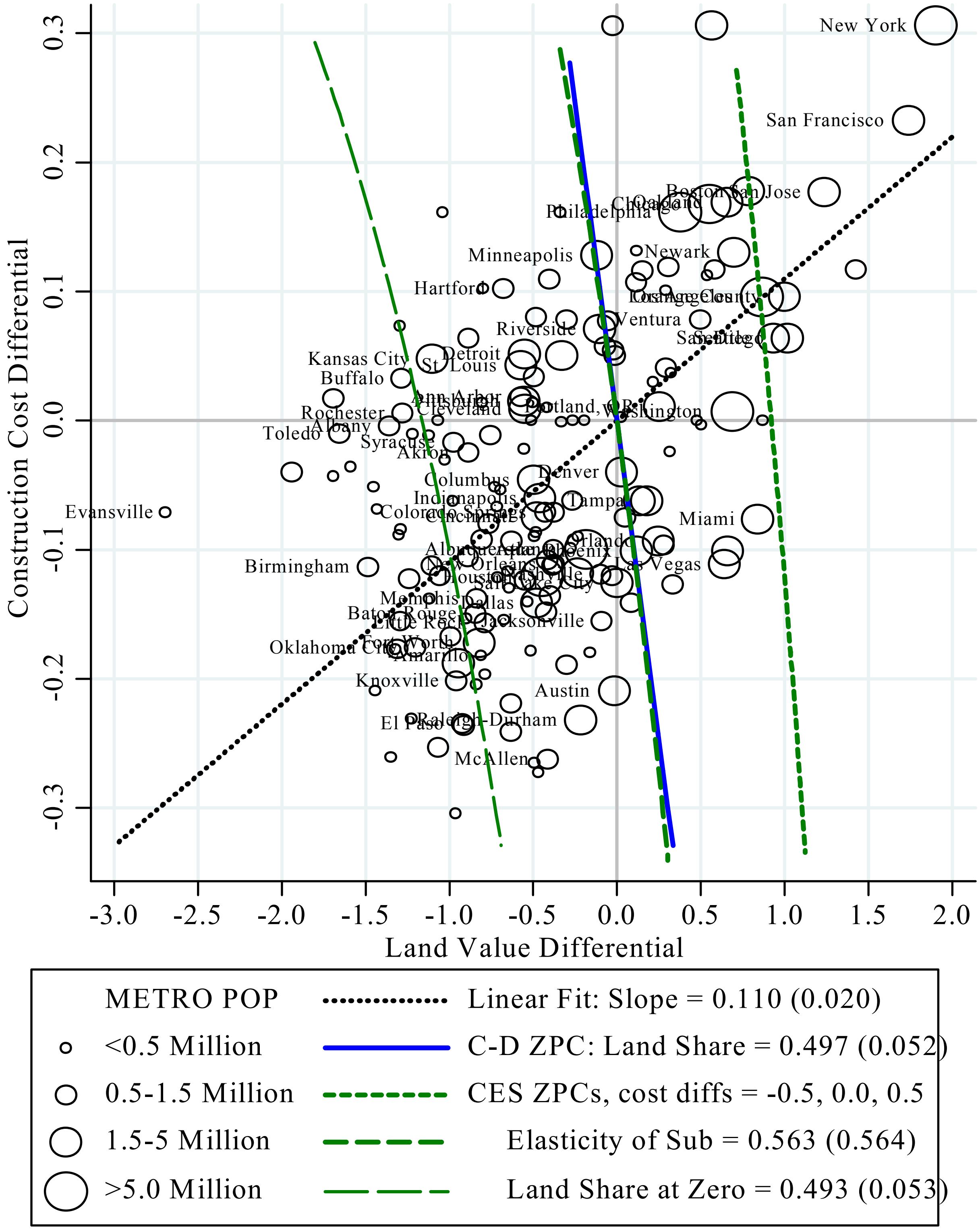
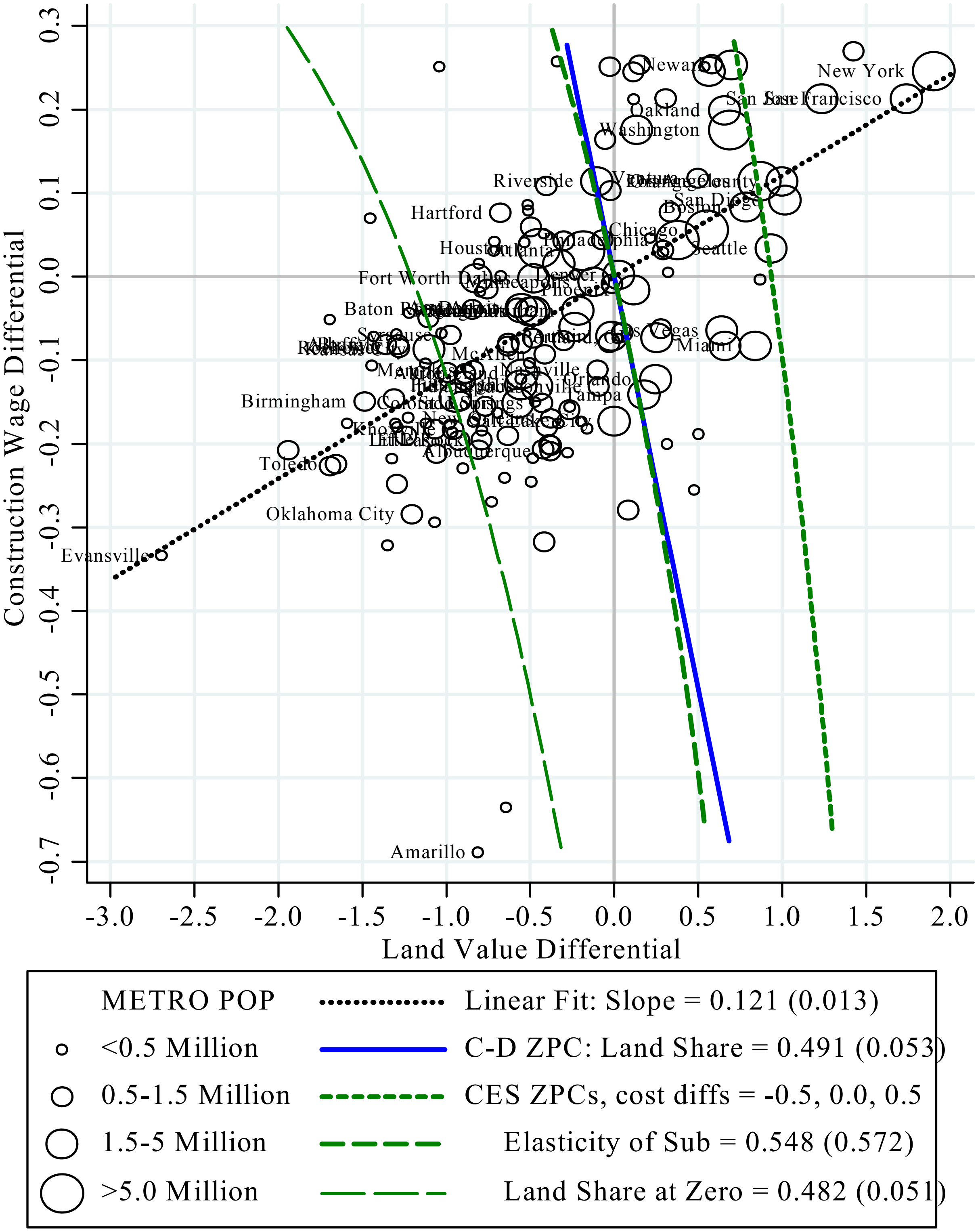
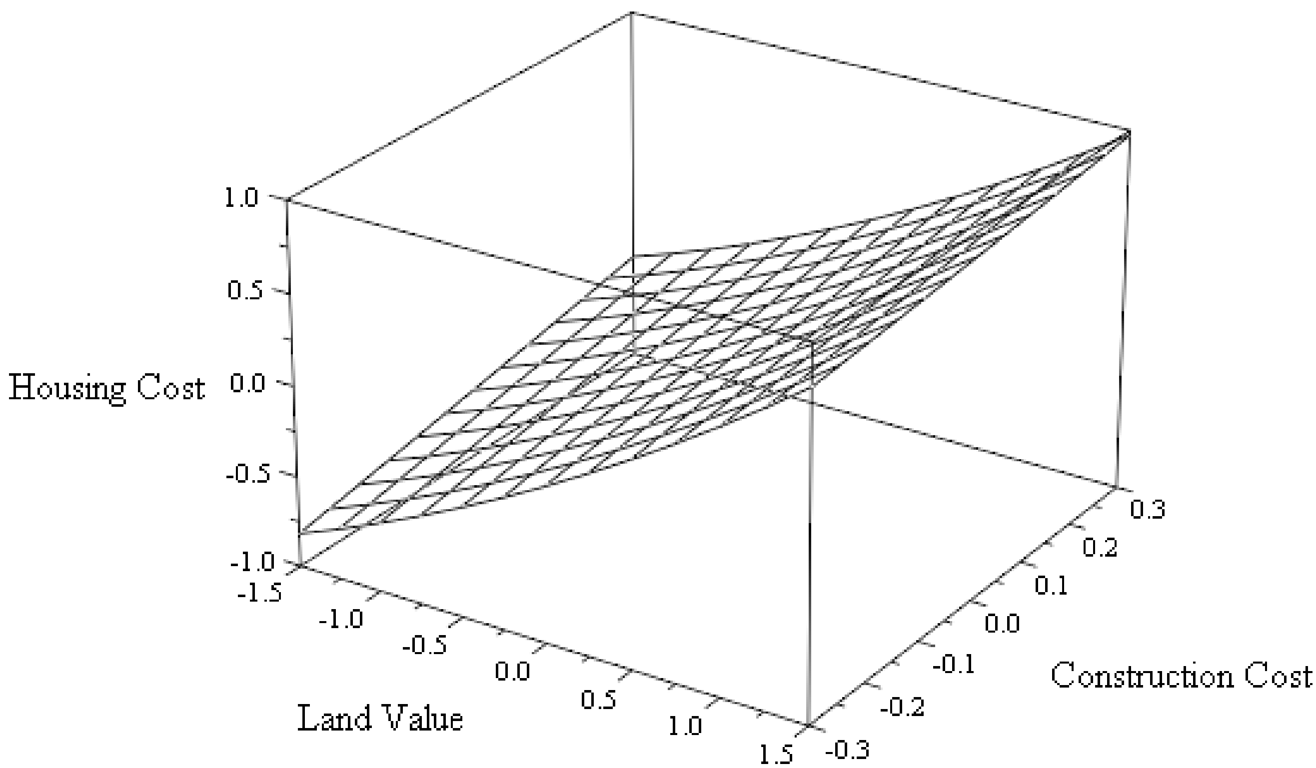


Figure 3B: Construction Wages vs. Land Values





1.0
0.5
Housing Cost
0.0
-0.5
-1.0
-1.5
-1.0
-0.5
0.0
0.5
1.0
1.5
Land Value
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
Construction Cost

Fig. 4: Productivity in the Tradeable and Housing Sectors

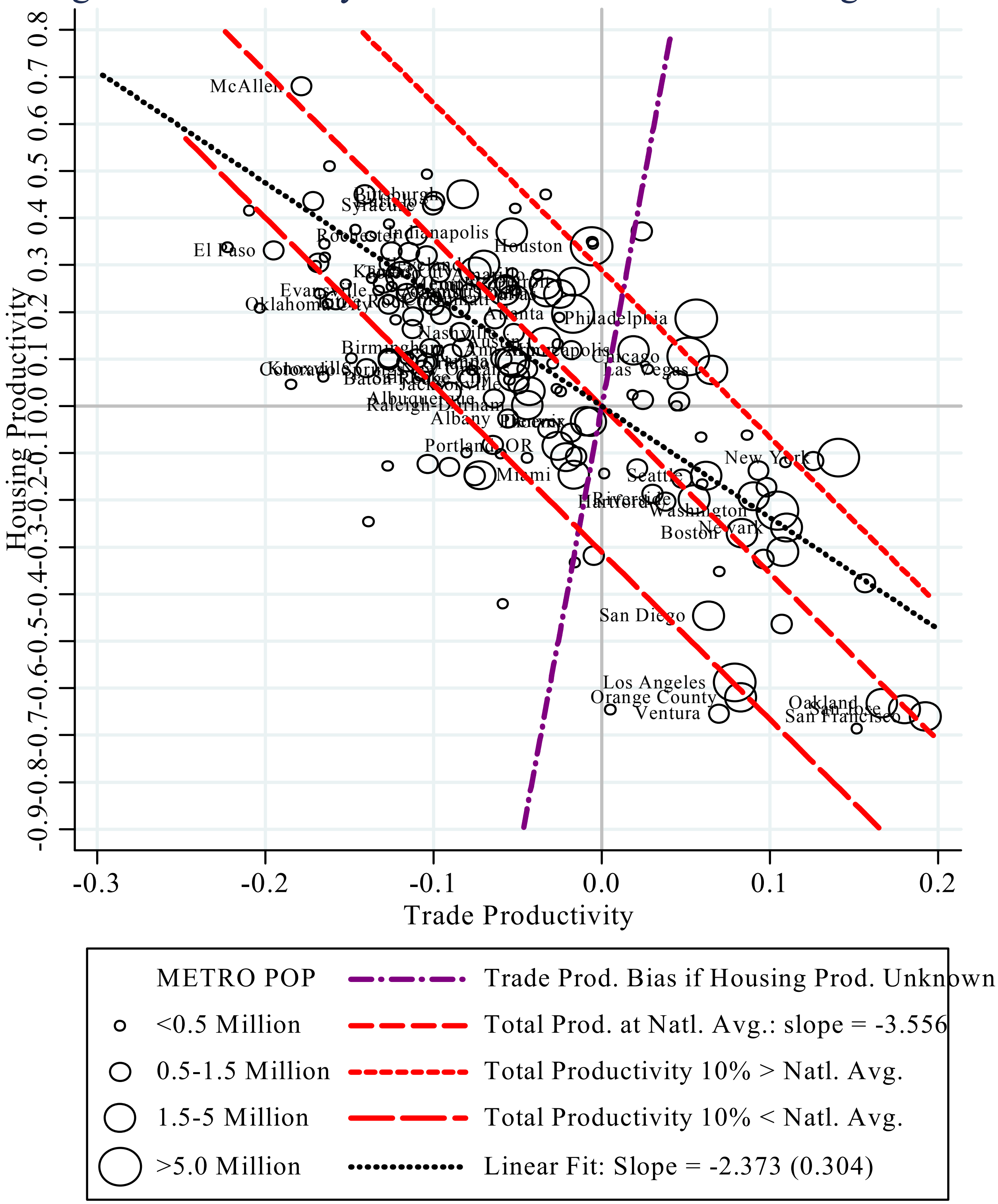


Figure 5: Quality of Life vs. Housing Productivity

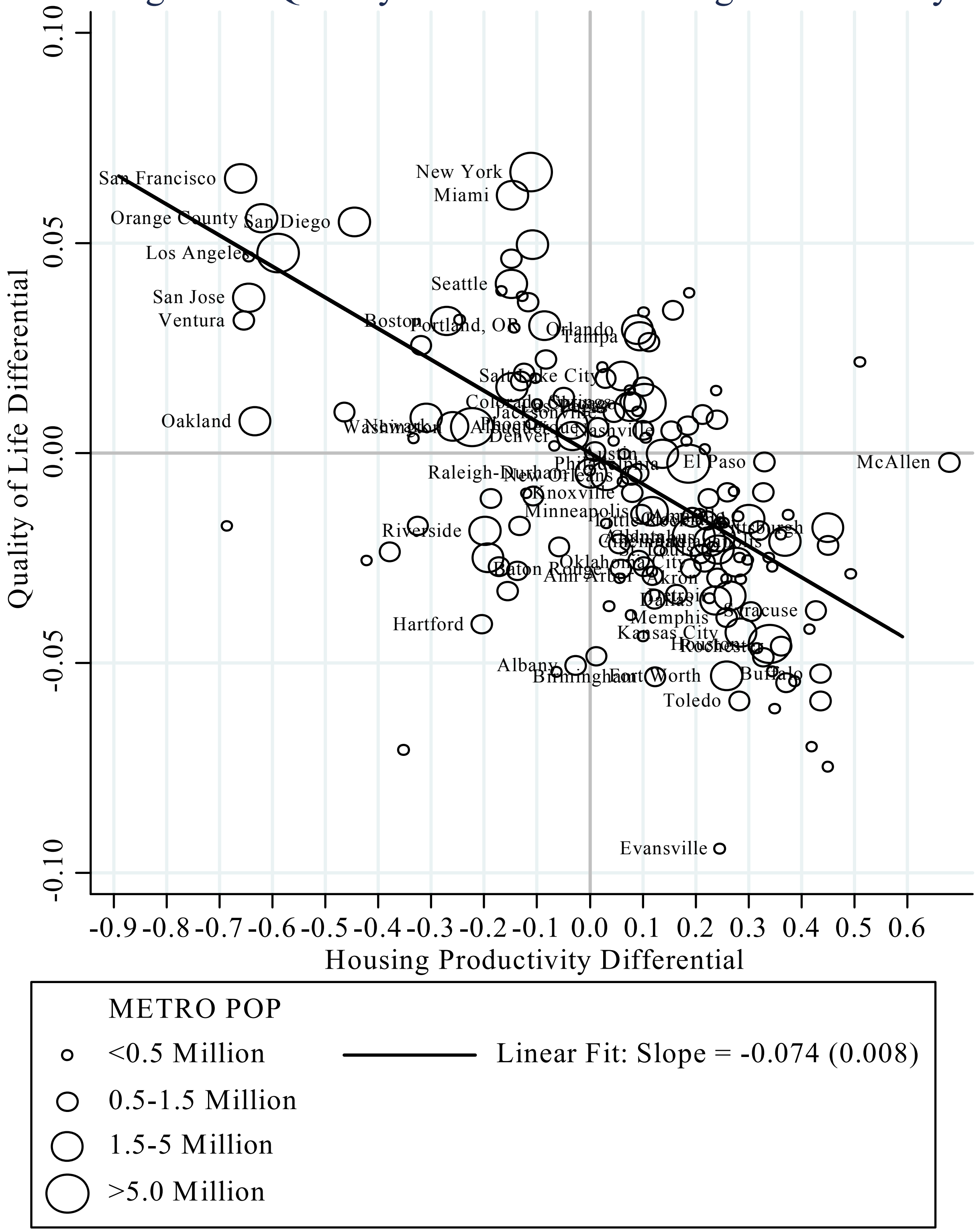


Figure A: Construction Costs vs. Construction Wages

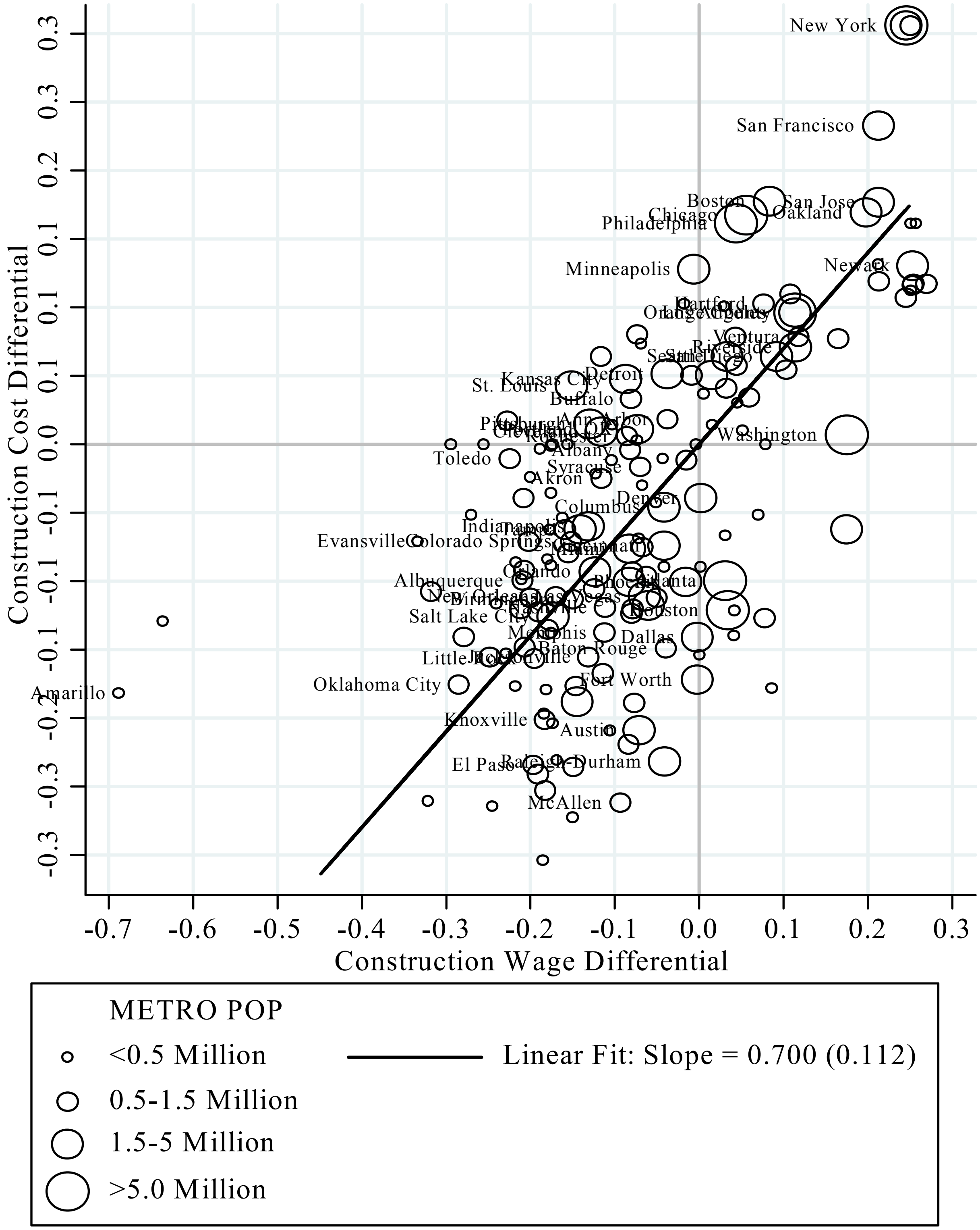


Figure B: Construction Wages vs. Overall Wages

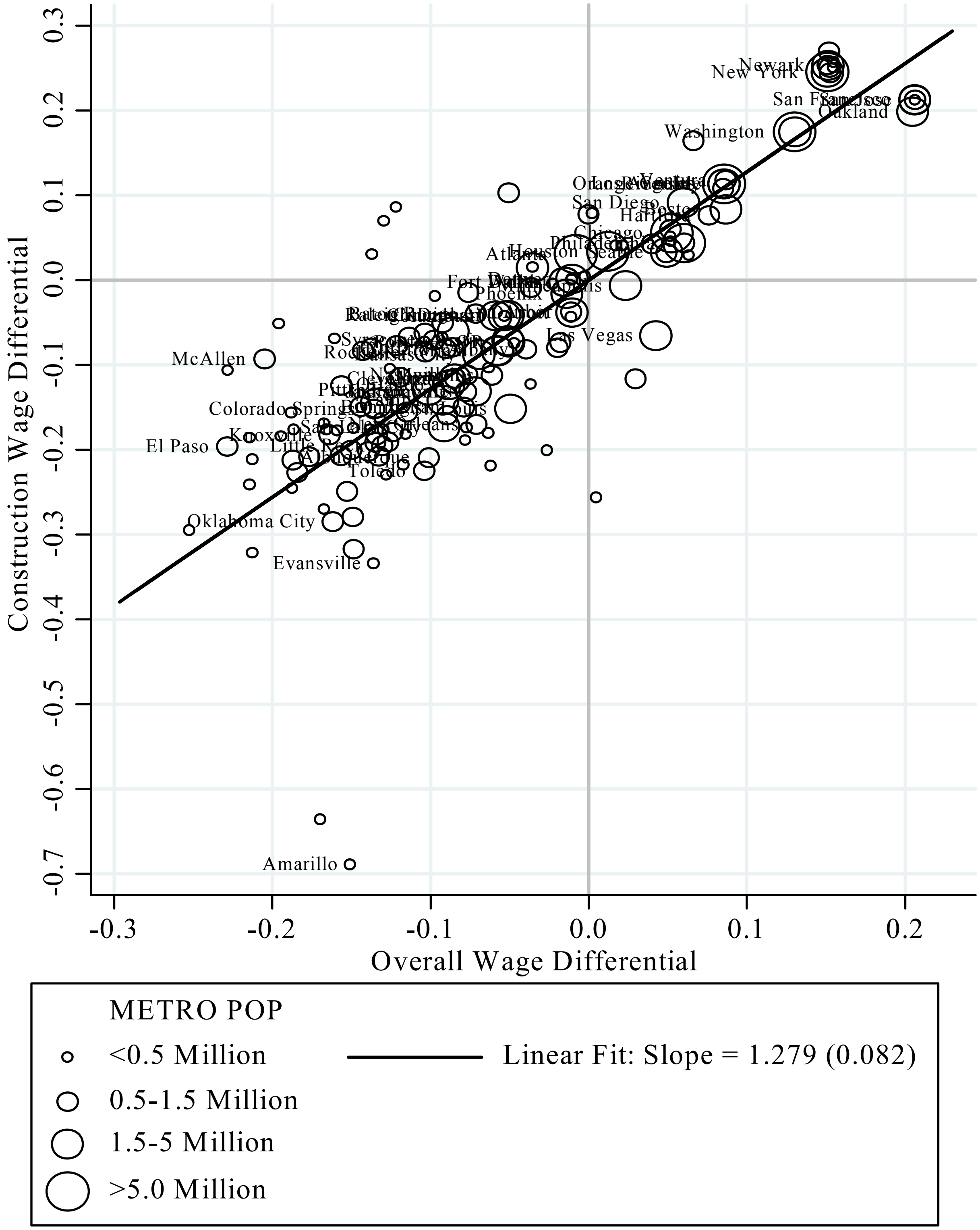


Figure C: Housing Prices vs. Housing Rents

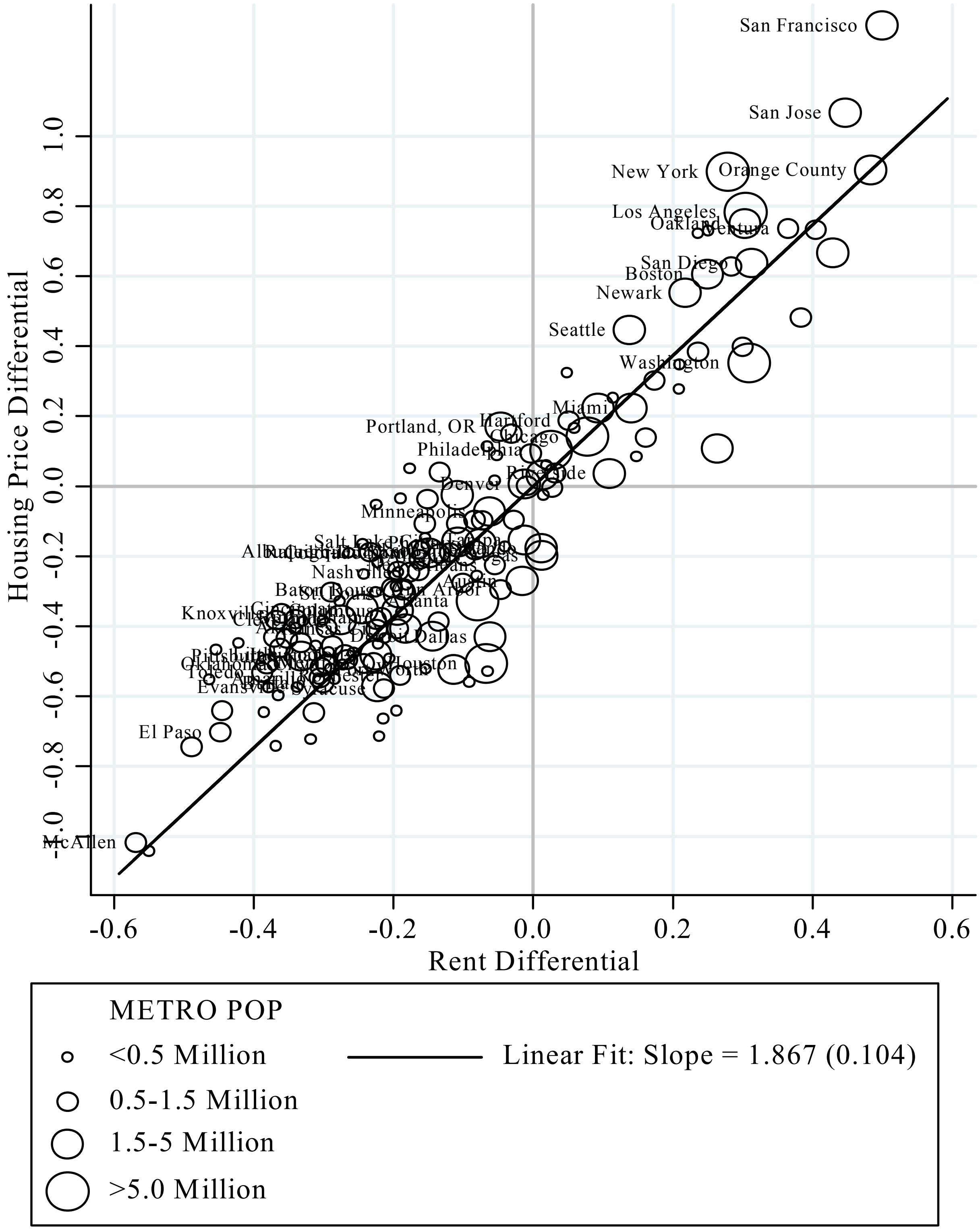


TABLE 1: LAND VALUE AUXILLIARY REGRESSION

	Dependent Variable: Log Price per Acre			
	(1)	(2)	(3)	(4)
Log lot size (acres)		-0.646	-0.645	-0.591
		(0.012)	(0.012)	(0.036)
No planned use			-0.203	-0.341
			(0.021)	(0.096)
Planned use: commercial			-0.387	-0.306
			(0.076)	(0.091)
Planned use: industrial			-0.315	-0.538
			(0.029)	(0.128)
Planned use: retail			0.269	0.194
			(0.018)	(0.024)
Planned use: single family			-0.026	-0.182
			(0.024)	(0.086)
Planned use: multi-family			-0.072	-0.163
			(0.041)	(0.142)
Planned use: office			0.074	0.188
			(0.032)	(0.077)
Planned use: apartment			0.465	0.344
			(0.054)	(0.149)
Planned use: hold for development			-0.074	-0.117
			(0.026)	(0.067)
Planned use: hold for investment			-0.339	-0.244
			(0.062)	(0.062)
Planned use: mixed use			0.377	0.412
			(0.046)	(0.079)
Planned use: medical			0.166	-0.079
			(0.039)	(0.099)
Planned use: parking			0.178	0.206
			(0.053)	(0.103)
Number of Observations	68,757	68,757	68,757	68,757
Adjusted R-squared	0.283	0.677	0.704	0.757
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 dummies for MSA/PMSA and quarter of sale (not shown). Predicted density is number of land sales predicted by a geographical model of housing units relative to city center; please see section 4.1, Land Values, for a full description.

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

Name of Area	Population	Observed No. of Land Sales	*Adjusted Differentials* Land Value	Housing Price	Wages (Const. Only)	*Raw Differentials* Regulation Index (z-score)	Geo Avail. Index (z-score)	Const. Cost Index	Land Value Rank
Metropolitan Areas:									
New York, NY PMSA	9,747,281	1,603	1.902	0.838	0.246	0.670	0.550	0.306	1
San Francisco, CA PMSA	1,785,097	152	1.738	1.284	0.213	0.782	2.152	0.232	2
Jersey City, NJ PMSA	597,924	43	1.426	0.560	0.269	0.087	0.226	0.117	3
San Jose, CA PMSA	1,784,642	217	1.237	1.077	0.213	-0.040	1.694	0.177	4
Orange County, CA PMSA	3,026,786	233	1.000	0.927	0.114	0.183	1.139	0.096	6
Washington, DC-MD-VA-WV PMSA	5,650,154	1,840	0.690	0.382	0.175	0.297	-0.746	0.007	13
Chicago, IL PMSA	8,710,824	3,511	0.551	0.136	0.056	-0.352	0.530	0.167	19
Philadelphia, PA-NJ PMSA	5,332,822	859	0.378	0.012	0.044	1.343	-0.932	0.161	24
Boston, MA-NH PMSA	3,552,421	122	0.784	0.581	0.083	2.253	0.231	0.178	11
Phoenix-Mesa, AZ MSA	4,364,094	5,946	0.116	-0.034	-0.016	0.645	-0.746	-0.101	38
Riverside-San Bernardino, CA PMSA	4,143,113	2,452	-0.105	0.215	0.114	0.465	0.426	0.071	55
Atlanta, GA MSA	5,315,841	5,229	-0.186	-0.330	0.031	-0.321	-1.229	-0.100	58
Detroit, MI PMSA	4,373,040	679	-0.554	-0.350	-0.038	-0.298	-0.229	0.051	99
Houston, TX PMSA	5,219,317	1,143	-0.447	-0.545	0.034	-0.986	-1.018	-0.121	82
Dallas, TX PMSA	4,399,895	811	-0.478	-0.466	-0.002	-0.744	-0.981	-0.141	86
Youngstown-Warren, OH MSA	554,614	49	-1.942	-0.796	-0.208	-0.982	-0.914	-0.040	170
Evansville-Henderson, IN-KY MSA	305,455	33	-2.695	-0.694	-0.334	-2.039	-1.005	-0.071	171
Saginaw-Bay City-Midland, MI MSA	390,032	41	-1.590	-0.691	-0.176	-0.391	-0.627	-0.036	166
Population Categories:									
Less than 500,000	57,630,737	3,597	-0.636	-0.313	-0.104	-0.355	-0.033	-0.060	4
500,000 to 1,500,000	232,990,833	13,558	-0.539	-0.229	-0.071	-0.280	-0.180	-0.059	3
1,500,000 to 5,000,000	491,452,831	31,981	0.108	0.063	0.006	0.090	0.165	0.005	2
5,000,000+	298,945,500	15,945	0.691	0.310	0.112	0.185	0.003	0.103	1
United States		29,671	0.851	0.509	0.152	0.959	1.008	0.141	
	total				*standard deviations (population weighted)*				

Land-value data from CoStar COMPS database for years 2005 to 2010. Wage and housing-cost data from 2005 to 2010 American Community Survey 1 percent samples. Wage differentials based on the average logarithm of hourly wages for full-time workers ages 25 to 55. Housing-price differentials based on the average logarithm of housing prices. Adjusted differentials are city-fixed effects from individual level regressions on extended sets of worker and housing covariates. Regulation Index is the Wharton Residential Land Use Regulatory Index (WRLURI) from Gyourko et al. (2008). Geographic Availability Index is the Land Unavailability Index, constructed by Saiz (2010) at the Primary Metropolitan Statistical Area level. These indices have been turned into z-scores by subtracting the mean and dividing by the standard deviation. Construction-cost differential from R.S. Means.

TABLE 3: MODEL OF HOUSING-COST DETERMINATION WITH CONSTANT NON-LAND INPUT PRICES

Specification	Basic Cobb-Douglas	CES	Rents Only	Housing Costs
Dependent Variable	Hous. Price	Hous. Price	Hous. Rent	Hous. Cost
	(1)	(2)	(3)	(4)
Land-Value Differential	0.333	0.328	0.159	0.262
	(0.028)	(0.031)	(0.025)	(0.034)
Land-Value Differential Squared		0.060	0.013	0.029
		(0.023)	(0.017)	(0.025)
Geographic Constraint Index: z-score	0.132	0.127	0.041	0.109
	(0.041)	(0.041)	(0.020)	(0.032)
Regulatory Index: z-score	0.112	0.119	0.053	0.111
	(0.018)	(0.017)	(0.013)	(0.016)
Constant	0.000	-0.039	-0.009	-0.019
	(0.035)	(0.041)	(0.024)	(0.035)
Number of Observations	688	688	688	688
Adjusted R-squared	0.755	0.773	0.676	0.780
Elasticity of Substitution	1.000	0.452	0.801	0.701
		(0.199)	(0.240)	(0.243)

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 2. Columns (1) and (2) use owner observations, column (3) uses renter observations, and column (4) uses owners and renters.

TABLE 4A: MODEL OF HOUSING-COST DETERMINATION WITH VARIABLE CONSTRUCTION COSTS

Specification	Basic Cobb-Douglas (1)	Restricted Cobb-Douglas (2)	Translog (3)	Restricted Translog (4)	Non-neutral Productivity Translog (5)	Calibrated Restricted Translog (6)
Land-Value Differential	0.262	0.273	0.262	0.278	0.274	0.400
	(0.033)	(0.031)	(0.038)	(0.036)	(0.036)	
Construction-Cost Differential	0.986	0.727	0.904	0.722	0.726	0.600
	(0.205)	(0.031)	(0.235)	(0.036)	(0.036)	
Land-Value Differential Squared			0.031	0.047	0.040	0.053
			(0.026)	(0.024)	(0.028)	(0.023)
Construction-Cost Differential Squared			-0.529	0.047	0.040	0.053
			(1.535)	(0.024)	(0.028)	(0.023)
Land-Value Differential X Construction-Cost Differential			0.130	-0.094	-0.080	-0.106
			(0.339)	(0.048)	(1.077)	(0.047)
Geographic Constraint Index: z-score	0.126	0.131	0.124	0.124	0.118	0.087
	(0.036)	(0.038)	(0.036)	(0.038)	(0.034)	(0.013)
Regulatory Index: z-score	0.081	0.091	0.088	0.094	0.096	0.067
	(0.021)	(0.016)	(0.019)	(0.016)	(0.017)	(0.010)
Geographic Constraint Index times Land Value Differential minus Construction Cost Differential					0.041	
					(0.040)	
Regulatory Index times Land Value Differential minus Construction Cost Differential					-0.019	
					(0.024)	
Constant	0.002	0.002	-0.017	-0.024	-0.029	-0.028
	(0.032)	(0.032)	(0.052)	(0.036)	(0.036)	(0.015)
Number of Observations	668	668	668	668	668	668
Adjusted R-squared	0.805	0.802	0.811	0.810	0.728	0.786
p -value for constant-returns-to-scale restrictions		0.217		0.893		
p -value for Cobb-Douglas restrictions	0.544	0.149				
p- value for all restrictions		0.130				
Elasticity of Substitution	1.000	1.000		0.530	0.597	0.578
				(0.223)	(0.268)	(0.201)

Dependent variable in all regressions is housing price measure. Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 2. Factor-cost restrictions that production function exhibits constant returns to scale. Cobb-Douglas restrictions that squared and interacted differential coefficients equal zero (elasticity of substitution between factors equals 1). Land-cost differential in column 6 calibrated to 0.4 and construction-cost differential calibrated to 0.6.

TABLE 4B: MODEL OF HOUSING-COST DETERMINATION WITH VARIABLE CONSTRUCTION WAGES

Specification	Basic Cobb-Douglas	Restricted Cobb-Douglas 1	Translog	Restricted Translog	Const. Cost Model	Restricted Cobb-Douglas 2	Non-neutral Productivity Translog	Calibrated Restricted Translog	Calibrated Cobb-Douglas
Dependent Variable	Hous. Price	Hous. Price	Hous. Price	Hous. Price	Const. Cost	Hous. Price	Hous. Price	Hous. Price	Hous. Price
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Land-Value Differential	0.251	0.258	0.231	0.260	0.025	0.281	0.256	0.400	0.400
	(0.024)	(0.026)	(0.031)	(0.029)	(0.019)	(0.027)	(0.029)		
Construction-Wage Differential	0.896	0.742	0.974	0.740	0.549	0.325	0.744	0.600	0.271
	(0.152)	(0.026)	(0.125)	(0.029)	(0.113)	(0.006)	(0.029)		
Implied Capital-Cost Differential	-0.147	0.000	-0.205	0.000	0.455	0.394	0.000	0.000	0.329
	(0.150)		(0.111)		(0.062)	(0.015)			
Land-Value Differential Squared			0.010	0.048			0.041	0.051	
			(0.023)	(0.020)			(.026)	(0.024)	
Construction-Wage Differential Squared			1.026	0.048			0.041	0.051	
			(0.404)	(0.020)			(.026)	(0.024)	
Land-Value Differential X Construction-Wage Differential			0.356	-0.096			-0.082	-0.101	
			(0.161)	(0.040)			(0.052)	(0.048)	
Geographic Constraint Index: z-score	0.149	0.148	0.146	0.143	0.018	0.144	0.138	0.099	0.106
	(0.032)	(0.033)	(0.030)	(0.034)	(0.014)	(0.036)	(0.031)	(0.012)	(0.012)
Regulatory Index: z-score	0.078	0.086	0.082	0.089	0.008	0.098	0.091	0.059	0.066
	(0.018)	(0.014)	(0.016)	(0.013)	(0.014)	(0.015)	(0.015)	(0.009)	(0.009)
Geographic Constraint Index times Land Value Differential minus Construction Cost Differential							-0.015		
							(0.024)		
Regulatory Index times Land Value Differential minus Construction Cost Differential							0.038		
							(0.037)		
Constant	0.000	0.000	-0.054	-0.026	0.000	0.000	-0.032	-0.027	0.000
	(0.027)	(0.028)	(0.034)	(0.031)	(0.014)	(0.031)	(0.029)	(0.015)	(0.011)
Number of Observations	688	688	688	688	171	688	688	688	688
Adjusted R-squared	0.808	0.806	0.832	0.815	0.523	0.786	0.816	0.785	1.000
p -value for constant-returns-to-scale restrictions		0.331		0.000		0.000			
p -value for Cobb-Douglas restrictions	0.000	0.018							
p- value for all restrictions		0.000							
Elasticity of Substitution	1.000	1.000		0.499	1.000		0.574	0.578	1.000
				(0.194)			(0.258)	(0.201)	

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 2. Factor-cost restrictions that production function exhibits constant returns to scale. Cobb-Douglas restrictions that squared and interacted differential coefficients equal zero (elasticity of substitution between factors equals one). Land-cost and construction-wage differentials calibrated to values shown in columns 8 and 9.

TABLE 5: MODEL OF HOUSING COSTS WITH DISAGGREGATED GEOGRAPHIC CONSTR
REGULATORY INDICES

Specification	Regulatory Index Factor Loading			Restricted Translog w Cons Cost
Dependent Variable		Reg Index	Geo Index	Hous. Price
		(1)	(2)	(3)
Land-Value Differential				0.227
				(0.024)
Land-Value Differential Squared				0.031
				(0.015)
Approval Delay: z-score	0.29	0.514		0.106
		(0.040)		(0.054)
Local Political Pressure: z-score	0.22	0.187		0.061
		(0.069)		(0.031)
State Political Involvement: z-score	0.22	0.386		0.058
		(0.023)		(0.020)
Open Space: z-score	0.18	0.134		0.024
		(0.084)		(0.060)
Exactions: z-score	0.15	-0.021		0.045
		(0.075)		(0.075)
Local Project Approval: z-score	0.15	0.215		-0.012
		(0.019)		(0.018)
Local Assembly: z-score	0.14	0.139		-0.025
		(0.046)		(0.027)
Density Restrictions: z-score	0.09	0.107		-0.065
		(0.091)		(0.064)
Supply Restrictions: z-score	0.02	-0.021		-0.013
		(0.086)		(0.066)
State Court Involvement: z-score	-0.03	-0.132		0.073
		(0.021)		(0.022)
Local Zoning Approval: z-score	-0.04	-0.102		-0.027
		(0.073)		(0.045)
Flat Land Share: z-score			-0.481	-0.100
			(0.036)	(0.031)
Solid Land Share: z-score			-0.790	-0.077
			(0.063)	(0.020)
Constant		0.000	0.000	-0.016
		(0.021)	(0.044)	(0.025)
Number of Observations		688	688	668
Adjusted R-squared		0.946	0.842	0.871
Elasticity of Substitution				0.641
				(0.159)

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Tab
constituent components of Wharton Residential Land Use Regulatory Index (WRLURI) from Gyourko
Constituent components of geographical index provided to the authors by Albert Saiz. Mean slope is b
authors' calculations at the Census tract level.

TABLE 6: INFERRED ATTRIBUTES OF SELECTED METROPOLITAN AREAS, RANKED BY TOTAL AMENITY VALUE

Name	*Productivity* Housing (Including Indices) (1)	Unexplained Housing Component (2)	Tradeables (3)	Quality of Life (4)	Total Amenity Value (5)
Metropolitan Areas:					
San Francisco, CA PMSA	-0.660	-0.025	0.192	0.065	0.070
New York, NY PMSA	-0.110	0.031	0.141	0.067	0.137
San Jose, CA PMSA	-0.645	-0.182	0.180	0.037	0.036
Jersey City, NJ PMSA	-0.117	-0.098	0.126	0.036	0.095
Oakland, CA PMSA	-0.632	-0.171	0.167	0.008	0.000
Washington, DC-MD-VA-WV PMSA	-0.222	-0.194	0.104	0.006	0.033
Boston, MA-NH PMSA	-0.271	0.017	0.083	0.031	0.036
Chicago, IL PMSA	0.105	0.032	0.052	0.012	0.064
Philadelphia, PA-NJ PMSA	0.186	0.115	0.056	-0.003	0.067
Riverside-San Bernardino, CA PMSA	-0.198	-0.026	0.055	-0.019	-0.019
Phoenix-Mesa, AZ MSA	-0.033	0.060	-0.007	0.007	-0.004
Atlanta, GA MSA	0.197	0.030	-0.017	-0.020	0.004
Dallas, TX PMSA	0.239	-0.034	-0.025	-0.035	-0.008
Houston, TX PMSA	0.340	0.103	-0.006	-0.046	0.012
Detroit, MI PMSA	0.264	0.238	-0.017	-0.034	0.003
Evansville-Henderson, IN-KY MSA	0.245	0.001	-0.133	-0.094	-0.135
Saginaw-Bay City-Midland, MI MSA	0.387	0.332	-0.126	-0.054	-0.066
Youngstown-Warren, OH MSA	0.436	0.048	-0.171	-0.059	-0.090
El Paso, TX MSA	0.330	-0.003	-0.195	-0.002	-0.067
Population Categories:					
Less than 500,000	0.114	0.049	-0.073	-0.014	-0.041
500,000 to 1,500,000	0.071	-0.019	-0.055	-0.014	-0.036
1,500,000 to 5,000,000	-0.038	0.006	0.011	0.004	0.004
5,000,000+	-0.068	-0.007	0.068	0.018	0.049
United States	0.287	0.135	0.082	0.034	0.048
	standard deviations (population weighted)				

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 2. Housing productivity in column 1 calculated from specification in Table 5, column 3 as the negative of the sum of the regression residual (reported in column 2) plus the housing price predicted by the WRLURI and Saiz subindices. Productivity in tradeables calculated as 0.825 times the overall wage differentials plus 0.025 times the land value differentials. Quality of Life calculated as 0.15 times the housing price differential plus 0.18 times the price differential of other non-tradeable goods minus 0.15 times the overall wage differential. Total Amenity Value differential calculated as 0.18 times the housing productivity differential plus 0.64 times the tradeable productivity differential plus the quality of life differential. Quality of Life and Total Amenity Value are expressed as a fraction of local household income.

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

	Dependent Variable			
	Tradeables Productivity (1)	Housing Productivity (2)	Unexplained Hous. Prod. (3)	Total Productivity (4)
Panel A: Population				
Log of Population	0.053	-0.108	-0.056	0.015
	(0.005)	(0.033)	(0.024)	(0.007)
Number of Observations	171	171	171	171
Adjusted R-squared	0.623	0.216	0.122	0.192
Panel B: Population Density				
Weighted Density Differential	0.065	-0.132	-0.066	0.018
	(0.005)	(0.045)	(0.032)	(0.007)
Number of Observations	171	171	171	171
Adjusted R-squared	0.476	0.166	0.086	0.143

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 2. Tradeables and Housing Productivity differentials calculated as in Table 6. Total Productivity calculated as 0.18 times Housing Productivity plus 0.64 times Tradeables Productivity. Weighted Density Differential calculated as the population density at the census tract level weighted by population.

TABLE 8: QUALITY OF LIFE AND HOUSING PRODUCTIVITY

	Dependent Variable: Quality of Life			
	Total Housing Productivity		Housing Productivity Predicted by Regulation	
	(1)	(2)	(3)	(4)
Housing Productivity	-0.040	-0.027	-0.060	-0.040
	(0.016)	(0.015)	(0.015)	(0.016)
Natural Controls	X	X	X	X
Artificial Controls		X		X
Number of Observations	165	165	165	165
Adjusted R-squared	0.55	0.75	0.56	0.75

Robust standard errors, clustered by CMSA, in parentheses. Quality of Life calculated as in Table 6. Housing Productivity predicted by regulation based upon the projection of housing costs on the subindices in column 3 of 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.

TABLE A1 (PROVISIONAL): LIST OF METROPOLITAN AREAS 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. Cost Index	Housing	Tradea-bles	Land Value Rank
Metropolitan Areas:														
New York, NY PMSA	9,747,281	2	1,603	1.902	1.525	0.838	0.151	0.246	0.670	0.550	0.306	-0.110	0.141	1
San Francisco, CA PMSA	1,785,097	9	152	1.738	1.375	1.284	0.206	0.213	0.782	2.152	0.232	-0.660	0.192	2
Jersey City, NJ PMSA	597,924	2	43	1.426	1.453	0.560	0.152	0.269	0.087	0.226	0.117	-0.117	0.126	3
San Jose, CA PMSA	1,784,642	9	217	1.237	1.230	1.077	0.206	0.213	-0.040	1.694	0.177	-0.645	0.180	4
San Diego, CA MSA	3,053,793	9	957	1.017	0.835	0.735	0.060	0.092	0.267	1.675	0.064	-0.446	0.064	5
Orange County, CA PMSA	3,026,786	9	233	1.000	1.137	0.927	0.086	0.114	0.183	1.139	0.096	-0.620	0.082	6
Seattle-Bellevue-Everett, WA PMSA	2,692,066	9	1,626	0.935	0.820	0.415	0.049	0.033	1.038	0.707	0.064	-0.148	0.062	7
Visalia-Tulare-Porterville, CA MSA	429,668	9	32	0.866	0.594	-0.204	-0.023	-0.004	0.357	-0.478	0.000	-0.143	0.002	8
Los Angeles-Long Beach, CA PMSA	9,848,011	9	1,760	0.864	0.916	0.858	0.086	0.114	0.381	1.139	0.096	-0.589	0.079	9
Miami, FL PMSA	2,500,625	5	1,233	0.840	0.853	0.283	-0.058	-0.083	1.133	2.323	-0.076	-0.147	-0.017	10
Boston, MA-NH PMSA	3,552,421	1	122	0.784	0.659	0.581	0.087	0.083	2.253	0.231	0.178	-0.271	0.083	11
Newark, NJ PMSA	2,045,344	2	142	0.696	0.379	0.511	0.151	0.254	0.708	0.064	0.130	-0.259	0.110	12
Washington, DC-MD-VA-WV PMSA	5,650,154	5	1,840	0.690	0.704	0.382	0.130	0.175	0.297	-0.746	0.007	-0.222	0.104	13
Fort Lauderdale, FL PMSA	1,766,476	5	741	0.661	0.766	0.178	-0.057	-0.083	0.776	2.277	-0.101	-0.109	-0.021	14
Oakland, CA PMSA	2,532,756	9	132	0.657	0.678	0.903	0.205	0.198	0.614	1.590	0.169	-0.632	0.167	15
Las Vegas, NV-AZ MSA	2,141,893	8	2,553	0.641	0.691	-0.019	0.043	-0.065	-1.475	0.141	-0.111	0.077	0.065	16
Bergen-Passaic, NJ PMSA	1,387,028	2	79	0.582	0.687	0.678	0.151	0.254	0.694	0.550	0.117	-0.464	0.107	17
Nassau-Suffolk, NY PMSA	2,875,904	2	396	0.563	0.611	0.660	0.151	0.245	0.750	0.550	0.306	-0.310	0.108	18
Chicago, IL PMSA	8,710,824	3	3,511	0.551	0.205	0.136	0.053	0.056	-0.352	0.530	0.167	0.105	0.052	19
Trenton, NJ PMSA	366,222	2	35	0.538	0.577	0.316	0.155	0.251	2.422	-0.852	0.112	-0.120	0.109	20
Madison, WI MSA	491,357	3	239	0.501	-0.200	-0.069	-0.078	-0.189	0.272	-0.874	-0.003	0.188	-0.025	21
Ventura, CA PMSA	802,983	9	131	0.496	0.603	0.816	0.086	0.118	1.549	2.470	0.078	-0.654	0.070	22
Naples, FL MSA	318,537	5	78	0.475	0.506	0.477	0.005	-0.256	0.088	2.273	0.000	-0.166	0.060	23
Philadelphia, PA-NJ PMSA	5,332,822	2	859	0.378	0.098	0.012	0.060	0.044	1.343	-0.932	0.161	0.186	0.056	24
West Palm Beach-Boca Raton, FL MSA	1,279,950	5	321	0.332	0.413	0.283	0.000	0.077	0.081	1.705	-0.127	-0.319	-0.005	25
San Luis Obispo-Atascadero-Paso Robles, CA MSA	266,971	9	43	0.323	0.395	0.732	-0.002	0.005	1.404	1.794	0.037	-0.645	0.005	26
Reno, NV MSA	414,820	8	57	0.317	0.207	0.020	-0.026	-0.200	-0.860	1.314	-0.024	0.023	0.018	27
Vallejo-Fairfield-Napa, CA PMSA	541,884	9	146	0.304	0.399	0.526	0.206	0.213	1.164	0.978	0.119	-0.377	0.156	28
Tacoma, WA PMSA	796,836	9	539	0.294	0.363	0.075	0.049	0.032	1.883	0.367	0.041	0.010	0.046	29
Atlantic-Cape May, NJ PMSA	367,803	2	37	0.289	-0.196	0.194	0.063	0.029	0.724	1.762	0.101	-0.067	0.059	30
Sarasota-Bradenton, FL MSA	688,126	5	601	0.279	0.362	0.125	-0.104	-0.062	1.096	1.833	-0.096	-0.149	-0.076	31
Portland-Vancouver, OR-WA PMSA	2,230,947	9	1,191	0.253	0.303	0.136	-0.050	-0.073	0.053	0.409	0.011	-0.085	-0.026	32
Orlando, FL MSA	2,082,421	5	1,612	0.247	0.327	-0.120	-0.089	-0.123	0.131	0.340	-0.093	0.091	-0.052	33
Olympia, WA PMSA	250,979	9	250	0.215	0.198	0.059	0.052	0.046	0.542	0.455	0.030	0.000	0.044	34
Tampa-St. Petersburg-Clearwater, FL MSA	2,747,272	5	1,220	0.178	0.224	-0.119	-0.092	-0.142	-0.722	0.609	-0.062	0.096	-0.054	35
Middlesex-Somerset-Hunterdon, NJ PMSA	1,247,641	2	101	0.150	0.288	0.441	0.151	0.254	1.417	0.550	0.116	-0.325	0.096	36
Baltimore, MD PMSA	2,690,886	5	802	0.135	0.173	0.161	0.130	0.175	2.160	-0.358	-0.062	-0.192	0.090	37
Phoenix-Mesa, AZ MSA	4,364,094	8	5,946	0.116	0.244	-0.034	-0.014	-0.016	0.645	-0.746	-0.101	-0.033	-0.007	38
Santa Rosa, CA PMSA	472,102	9	153	0.114	0.512	0.813	0.206	0.213	1.737	1.655	0.131	-0.686	0.152	39
New Haven-Meriden, CT PMSA	558,692	1	43	0.114	-0.141	0.272	0.153	0.245	-0.366	0.774	0.107	-0.172	0.098	40
Provo-Orem, UT MSA	545,307	8	47	0.083	0.237	-0.260	-0.149	-0.279	-0.041	1.488	-0.141	0.157	-0.084	41
Melbourne-Titusville-Palm Bay, FL MSA	536,357	5	420	0.047	0.055	-0.174	-0.113	-0.067	0.455	1.717	-0.075	0.112	-0.089	42
Denver, CO PMSA	2,445,781	8	2,015	0.029	-0.065	-0.006	-0.011	0.002	0.991	-0.610	-0.040	-0.032	-0.009	43
Salem, OR PMSA	396,103	9	54	0.020	-0.207	-0.096	-0.047	-0.074	0.273	0.189	0.003	0.091	-0.029	44
Salt Lake City-Ogden, UT MSA	1,567,650	8	145	0.000	0.084	-0.174	-0.091	-0.173	-0.421	2.095	-0.126	0.062	-0.053	45
Springfield, MA MSA	609,993	1	28	-0.014	-0.223	0.069	-0.037	-0.009	0.712	-0.103	0.050	-0.049	-0.032	46
Austin-San Marcos, TX MSA	1,705,075	7	384	-0.015	-0.352	-0.310	-0.051	-0.071	-0.824	-1.245	-0.209	0.137	-0.034	47
Allentown-Bethlehem-Easton, PA MSA	706,374	2	85	-0.023	0.066	-0.158	-0.051	0.103	-0.341	-0.408	0.054	0.185	-0.064	48

TABLE A1 (PROVISIONAL): LIST OF METROPOLITAN AREAS BY LAND PRICE DIFFERENTIAL, 2005-2010

				Adjusted Differentials					*Raw Differentials*			*Productivity*		
Full Name	Population	Cen-sus Div-ision	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. Cost Index	Housing	Tradea-bles	Land Value Rank
Monmouth-Ocean, NJ PMSA	1,217,783	2	124	-0.028	0.045	0.364	0.152	0.251	2.151	0.550	0.306	-0.137	0.093	49
Fort Myers-Cape Coral, FL MSA	586,908	5	294	-0.029	0.132	-0.033	-0.086	-0.079	-0.611	1.173	-0.120	-0.083	-0.065	50
Stockton-Lodi, CA MSA	674,860	9	163	-0.053	0.062	0.222	0.066	0.164	0.567	-0.839	0.077	-0.187	0.030	51
Wilmington-Newark, DE-MD PMSA	635,430	5	107	-0.071	0.016	-0.034	0.060	0.044	0.373	-0.711	0.057	0.055	0.045	52
Jacksonville, FL MSA	1,301,808	5	793	-0.092	0.088	-0.202	-0.078	-0.132	-0.408	0.888	-0.155	0.045	-0.050	53
Nashville, TN MSA	1,495,419	6	455	-0.098	-0.175	-0.284	-0.077	-0.111	-1.020	-0.801	-0.119	0.155	-0.052	54
Riverside-San Bernardino, CA PMSA	4,143,113	9	2,452	-0.105	-0.008	0.215	0.086	0.114	0.465	0.426	0.071	-0.198	0.055	55
Minneapolis-St. Paul, MN-WI MSA	3,269,814	4	846	-0.121	-0.009	-0.058	0.023	-0.006	-0.099	-0.488	0.128	0.118	0.019	56
Savannah, GA MSA	343,092	5	64	-0.164	-0.178	-0.264	-0.116	-0.182	-1.208	1.513	-0.180	0.076	-0.077	57
Atlanta, GA MSA	5,315,841	5	5,229	-0.186	-0.178	-0.330	-0.008	0.031	-0.321	-1.229	-0.100	0.197	-0.017	58
Fort Pierce-Port St. Lucie, FL MSA	406,296	5	71	-0.196	-0.087	-0.173	-0.077	-0.174	0.337	1.749	0.000	-0.110	-0.045	59
Raleigh-Durham-Chapel Hill, NC MSA	1,589,388	5	782	-0.219	-0.128	-0.242	-0.051	-0.041	0.425	-1.032	-0.232	0.002	-0.044	60
Boulder-Longmont, CO PMSA	311,786	8	183	-0.234	-0.070	0.199	-0.011	0.002	3.767	0.683	-0.090	-0.333	-0.016	61
Norfolk-Virginia Beach-Newport News, VA- MSA	1,667,410	5	392	-0.235	-0.175	-0.005	-0.086	-0.061	-0.182	1.497	-0.118	-0.148	-0.072	62
Myrtle Beach, SC MSA	263,868	5	84	-0.264	-0.660	-0.233	-0.188	-0.156	-1.697	1.599	0.000	0.101	-0.149	63
Lancaster, PA MSA	507,766	2	57	-0.267	-0.413	-0.222	-0.089	-0.159	0.088	-0.846	-0.062	0.101	-0.060	64
Springfield, MO MSA	383,637	4	43	-0.280	-0.715	-0.630	-0.213	-0.211	-1.570	-1.105	-0.099	0.510	-0.162	65
Modesto, CA MSA	510,385	9	142	-0.300	-0.174	0.118	0.040	0.043	0.021	-0.730	0.078	-0.133	0.021	66
Charleston-North Charleston, SC MSA	659,191	5	214	-0.300	-0.330	-0.102	-0.122	-0.077	-1.657	1.530	-0.189	-0.124	-0.103	67
Milwaukee-Waukesha, WI PMSA	1,559,667	3	399	-0.329	-0.462	-0.071	-0.036	0.015	0.355	0.616	0.050	0.031	-0.043	68
Eugene-Springfield, OR MSA	351,109	9	36	-0.333	-0.279	0.044	-0.166	-0.176	0.174	1.631	-0.001	-0.128	-0.127	69
Newburgh, NY-PA PMSA	444,061	2	54	-0.341	-0.065	0.113	0.155	0.257	-0.446	0.038	0.161	-0.063	0.086	70
Lakeland-Winter Haven, FL MSA	583,403	5	561	-0.375	-0.175	-0.363	-0.139	-0.202	-0.091	0.146	-0.071	0.214	-0.100	71
New Orleans, LA MSA	1,211,035	7	66	-0.377	-0.238	-0.253	-0.071	-0.170	-2.348	2.237	-0.111	0.078	-0.044	72
Albuquerque, NM MSA	841,428	8	114	-0.378	-0.016	-0.187	-0.101	-0.209	0.222	-0.860	-0.100	0.015	-0.064	73
Boise City, ID MSA	571,271	8	106	-0.386	-0.505	-0.281	-0.150	-0.201	-1.110	0.350	-0.112	0.101	-0.110	74
Tucson, AZ MSA	1,020,200	8	1,749	-0.400	-0.290	-0.075	-0.124	-0.179	2.045	-0.300	-0.135	-0.130	-0.090	75
Worcester, MA-CT PMSA	547,274	1	56	-0.404	-0.363	0.146	0.085	0.108	3.167	0.231	0.110	-0.155	0.048	76
McAllen-Edinburg-Mission, TX MSA	741,152	7	61	-0.414	-0.366	-0.989	-0.205	-0.093	-1.088	-1.384	-0.262	0.679	-0.178	77
Kenosha, WI PMSA	165,382	3	58	-0.418	-0.142	-0.171	0.052	0.051	0.984	0.916	0.010	0.078	0.027	78
Daytona Beach, FL MSA	587,512	5	93	-0.419	-0.047	-0.202	-0.149	-0.317	0.389	1.534	-0.108	0.030	-0.090	79
Chattanooga, TN-GA MSA	510,388	6	51	-0.424	-0.400	-0.461	-0.157	-0.207	-1.521	-0.165	-0.148	0.240	-0.116	80
Colorado Springs, CO MSA	604,542	8	892	-0.426	-0.258	-0.235	-0.135	-0.152	1.010	-0.339	-0.071	0.077	-0.106	81
Houston, TX PMSA	5,219,317	7	1,143	-0.447	-0.400	-0.545	0.012	0.034	-0.986	-1.018	-0.121	0.340	-0.006	82
Indianapolis, IN MSA	1,823,690	3	193	-0.461	-0.463	-0.527	-0.072	-0.132	-1.463	-1.359	-0.060	0.369	-0.053	83
Fayetteville-Springdale-Rogers, AR MSA	425,685	7	43	-0.468	-0.312	-0.436	-0.144	-0.150	-1.017	-0.013	-0.273	0.105	-0.115	84
Cincinnati, OH-KY-IN PMSA	1,776,911	3	637	-0.476	-0.436	-0.399	-0.053	-0.042	-1.339	-0.925	-0.074	0.227	-0.053	85
Dallas, TX PMSA	4,399,895	7	811	-0.478	-0.442	-0.466	-0.015	-0.002	-0.744	-0.981	-0.141	0.239	-0.025	86
Fresno, CA MSA	1,063,899	9	137	-0.483	-0.326	0.060	-0.018	-0.073	1.074	-0.799	0.080	-0.107	-0.015	87
Fort Collins-Loveland, CO MSA	298,382	8	344	-0.485	-0.326	-0.083	-0.117	-0.217	0.940	0.101	-0.086	-0.100	-0.080	88
Hamilton-Middletown, OH PMSA	363,184	3	151	-0.493	-0.317	-0.471	-0.053	-0.042	-0.335	-1.087	-0.090	0.283	-0.053	89
Gary, IN PMSA	657,809	3	111	-0.495	-0.528	-0.460	0.052	0.060	-1.479	0.114	0.034	0.371	0.024	90
Asheville, NC MSA	251,894	5	41	-0.495	-0.348	-0.079	-0.187	-0.245	-1.346	1.875	-0.265	-0.247	-0.139	91
Columbus, OH MSA	1,718,303	3	671	-0.498	-0.395	-0.398	-0.059	-0.042	0.041	-1.307	-0.046	0.244	-0.058	92
Reading, PA MSA	407,125	2	36	-0.504	0.207	-0.342	-0.063	-0.103	0.505	-0.622	0.014	0.246	-0.052	93
Merced, CA MSA	245,321	9	64	-0.512	-0.387	0.065	0.002	0.079	0.644	-0.932	0.000	0.032	-0.024	94
Biloxi-Gulfport-Pascagoula, MS MSA	355,075	6	30	-0.515	-0.925	-0.537	-0.122	0.086	-1.952	1.120	-0.178	0.272	-0.137	95
Galveston-Texas City, TX PMSA	286,814	7	39	-0.534	-0.632	-0.583	0.017	0.041	0.671	2.248	-0.140	0.345	-0.005	96
Cleveland-Lorain-Elyria, OH PMSA	2,192,053	3	416	-0.551	-0.415	-0.420	-0.084	-0.116	-0.622	0.554	0.009	0.300	-0.070	97
Richmond-Petersburg, VA MSA	1,119,459	5	399	-0.551	-0.446	-0.161	-0.020	-0.080	-0.975	-0.998	-0.124	-0.057	-0.018	98

TABLE A1 (PROVISIONAL): LIST OF METROPOLITAN AREAS 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. Cost Index	Housing	Tradeables	Land Value Rank
Detroit, MI PMSA	4,373,040	3	679	-0.554	-0.509	-0.350	-0.010	-0.038	-0.298	-0.229	0.051	0.264	-0.017	99
York, PA MSA	428,937	2	47	-0.556	-0.395	-0.278	-0.037	-0.122	1.015	-0.837	-0.022	0.132	-0.026	100
Pittsburgh, PA MSA	2,287,106	2	240	-0.557	-0.731	-0.562	-0.101	-0.130	-0.216	0.041	0.015	0.450	-0.083	101
St. Louis, MO-IL MSA	2,733,694	4	364	-0.573	-0.601	-0.338	-0.049	-0.152	-1.421	-0.887	0.043	0.242	-0.033	102
Ann Arbor, MI PMSA	630,518	3	136	-0.574	-0.828	-0.234	-0.011	-0.037	0.198	-0.954	0.018	0.119	-0.018	103
Omaha, NE-IA MSA	799,130	4	118	-0.631	-0.562	-0.543	-0.137	-0.080	-1.263	-1.266	-0.093	0.328	-0.125	104
Greensboro--Winston Salem--High Point, NC MSA	1,416,374	5	438	-0.633	-0.494	-0.428	-0.135	-0.191	-0.969	-1.276	-0.241	0.092	-0.104	105
Tulsa, OK MSA	873,304	7	245	-0.633	-0.540	-0.576	-0.143	-0.083	-1.561	-1.121	-0.219	0.260	-0.130	106
Gainesville, FL MSA	243,574	5	34	-0.644	-0.159	-0.148	-0.170	-0.636	-0.258	-0.675	-0.130	-0.102	-0.060	107
Lincoln, NE MSA	281,531	4	24	-0.654	-0.171	-0.481	-0.214	-0.241	0.840	-1.352	-0.117	0.239	-0.168	108
Greeley, CO PMSA	254,759	8	320	-0.676	-0.379	-0.307	-0.011	0.001	-0.471	-0.936	-0.154	0.036	-0.027	109
Hartford, CT MSA	1,231,125	1	101	-0.680	-0.749	0.141	0.076	0.076	0.385	-0.289	0.102	-0.204	0.038	110
Spokane, WA MSA	468,684	9	55	-0.695	-0.587	-0.262	-0.132	-0.163	0.722	-0.091	-0.054	0.064	-0.108	111
Brazoria, TX PMSA	309,208	7	62	-0.716	-0.842	-0.602	0.021	0.041	-1.199	-1.018	-0.121	0.350	-0.006	112
Canton-Massillon, OH MSA	408,005	3	40	-0.719	-0.805	-0.588	-0.137	0.030	-1.659	-0.813	-0.067	0.375	-0.146	113
La Crosse, WI-MN MSA	132,923	3	21	-0.732	-0.476	-0.386	-0.167	-0.270	0.285	0.323	-0.051	0.183	-0.123	114
Harrisburg-Lebanon-Carlisle, PA MSA	667,425	2	89	-0.757	-0.542	-0.379	-0.076	-0.015	0.438	-0.253	-0.012	0.209	-0.085	115
Louisville, KY-IN MSA	1,099,588	6	126	-0.765	-0.634	-0.425	-0.115	-0.155	-1.114	-0.808	-0.080	0.194	-0.096	116
Bryan-College Station, TX MSA	179,992	7	34	-0.787	-0.815	-0.549	-0.194	-0.184	0.240	-1.115	-0.197	0.218	-0.163	117
Little Rock-North Little Rock, AR MSA	657,416	7	110	-0.788	-0.921	-0.518	-0.130	-0.195	-1.725	-0.758	-0.157	0.221	-0.103	118
Rockford, IL MSA	409,058	3	104	-0.799	-0.667	-0.577	-0.097	-0.018	-1.217	-1.322	0.102	0.493	-0.104	119
Racine, WI PMSA	200,601	3	80	-0.806	-0.685	-0.212	-0.036	0.016	-0.711	1.220	0.014	0.057	-0.055	120
Dayton-Springfield, OH MSA	933,312	3	116	-0.809	-0.684	-0.568	-0.133	-0.207	-1.105	-1.378	-0.092	0.320	-0.104	121
Amarillo, TX MSA	238,299	7	27	-0.812	-0.846	-0.604	-0.151	-0.689	-1.008	-1.258	-0.182	0.280	-0.038	122
Fort Worth-Arlington, TX PMSA	2,113,278	7	506	-0.822	-0.653	-0.574	-0.015	-0.002	-0.782	-1.189	-0.172	0.258	-0.034	123
Memphis, TN-AR-MS MSA	1,230,253	6	173	-0.836	-0.689	-0.549	-0.061	-0.112	1.509	-0.833	-0.138	0.259	-0.057	124
Montgomery, AL MSA	354,108	6	33	-0.839	-1.317	-0.601	-0.149	-0.174	-1.953	-0.903	-0.204	0.253	-0.125	125
Baton Rouge, LA MSA	685,419	7	99	-0.843	-0.606	-0.357	-0.071	-0.039	-1.669	0.212	-0.149	0.058	-0.078	126
Bakersfield, CA MSA	807,407	9	64	-0.886	-0.661	-0.141	0.030	-0.116	0.257	-0.244	0.064	0.013	0.024	127
Akron, OH PMSA	699,935	3	169	-0.887	-0.667	-0.447	-0.084	-0.116	-0.265	-1.113	-0.025	0.241	-0.078	128
Fort Wayne, IN MSA	528,408	3	39	-0.889	-0.799	-0.724	-0.156	-0.125	-2.316	-1.304	-0.105	0.450	-0.141	129
Jackson, MS MSA	483,852	6	43	-0.902	-0.866	-0.548	-0.128	-0.229	-1.536	-0.875	-0.153	0.232	-0.098	130
Columbia, SC MSA	627,630	5	139	-0.914	-1.128	-0.469	-0.144	-0.149	-1.591	-0.684	-0.236	0.097	-0.127	131
El Paso, TX MSA	751,296	7	94	-0.925	-0.772	-0.718	-0.229	-0.196	0.787	-1.178	-0.235	0.330	-0.195	132
San Antonio, TX MSA	1,928,154	7	348	-0.946	-0.897	-0.628	-0.134	-0.145	-0.712	-1.274	-0.188	0.277	-0.119	133
Knoxville, TN MSA	785,490	6	193	-0.960	-0.790	-0.446	-0.164	-0.183	-0.966	0.457	-0.202	0.080	-0.140	134
Hickory-Morganton-Lenoir, NC MSA	365,364	5	88	-0.962	-0.810	-0.491	-0.214	-0.186	-1.292	-0.403	-0.304	0.046	-0.185	135
Syracuse, NY MSA	725,610	2	65	-0.977	-1.384	-0.627	-0.098	-0.070	-1.307	-0.555	-0.017	0.428	-0.100	136
Kalamazoo-Battle Creek, MI MSA	462,250	3	31	-0.980	-1.081	-0.615	-0.159	-0.177	-0.240	-0.946	-0.062	0.361	-0.137	137
Augusta-Aiken, GA-SC MSA	516,357	5	66	-0.992	-1.037	-0.530	-0.119	-0.115	-2.113	-0.918	-0.167	0.191	-0.112	138
Green Bay, WI MSA	247,319	3	49	-1.028	-0.668	-0.352	-0.093	-0.068	0.541	-0.289	-0.030	0.117	-0.097	139
Dutchess County, NY PMSA	293,562	2	33	-1.041	-0.790	0.278	0.155	0.251	0.194	0.550	0.161	-0.352	0.070	140
Lexington, KY MSA	554,107	6	29	-1.057	-0.817	-0.539	-0.187	-0.212	-0.075	-1.140	-0.120	0.224	-0.158	141
Greenville-Spartanburg-Anderson, SC MSA	1,096,009	5	507	-1.067	-1.023	-0.517	-0.134	-0.183	-1.863	-0.799	-0.253	0.093	-0.116	142
Brownsville-Harlingen-San Benito, TX MSA	396,371	7	52	-1.069	-1.046	-1.015	-0.253	-0.294	-1.896	-0.077	0.000	0.208	-0.203	143
Kansas City, MO-KS MSA	2,005,888	4	477	-1.103	-0.753	-0.462	-0.070	-0.087	-1.636	-1.145	0.048	0.285	-0.075	144
Des Moines, IA MSA	536,664	4	99	-1.106	-0.954	-0.428	-0.092	-0.050	-1.712	-1.127	-0.112	0.123	-0.102	145
Pensacola, FL MSA	455,102	5	102	-1.122	-0.999	-0.397	-0.187	-0.176	-1.738	1.145	-0.138	0.062	-0.165	146
Lansing-East Lansing, MI MSA	453,603	3	40	-1.124	-1.242	-0.518	-0.126	-0.104	-0.066	-1.093	-0.012	0.285	-0.123	147
Oklahoma City, OK MSA	1,213,704	7	395	-1.206	-1.042	-0.588	-0.162	-0.285	-0.916	-1.309	-0.176	0.217	-0.127	148

TABLE A1 (PROVISIONAL): LIST OF METROPOLITAN AREAS 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. Cost Index	Housing	Tradeables	Land Value Rank
Flint, MI PMSA	424,043	3	85	-1.222	-1.088	-0.693	-0.011	-0.043	-0.875	-0.960	-0.010	0.450	-0.033	149
Corpus Christi, TX MSA	391,269	7	74	-1.229	-1.105	-0.693	-0.167	-0.169	-0.764	0.432	-0.231	0.259	-0.152	150
Grand Rapids-Muskegon-Holland, MI MSA	1,157,672	3	121	-1.240	-1.219	-0.508	-0.127	-0.191	-0.594	-0.975	-0.123	0.164	-0.112	151
Rochester, NY MSA	1,093,434	2	110	-1.279	-1.960	-0.598	-0.103	-0.085	-0.464	0.062	0.006	0.362	-0.110	152
Buffalo-Niagara Falls, NY MSA	1,123,804	2	104	-1.286	-1.143	-0.653	-0.090	-0.081	-0.696	-0.497	0.033	0.436	-0.099	153
Portland, ME MSA	256,178	1	25	-1.293	-1.401	0.101	-0.064	-0.180	1.711	0.992	-0.084	-0.421	-0.059	154
Mobile, AL MSA	591,599	6	135	-1.293	-1.165	-0.482	-0.152	-0.249	-1.964	0.006	-0.155	0.102	-0.127	155
Duluth-Superior, MN-WI MSA	242,041	4	22	-1.296	-1.119	-0.530	-0.161	-0.069	-0.958	0.256	0.073	0.345	-0.165	156
Cedar Rapids, IA MSA	209,226	4	33	-1.301	-1.129	-0.550	-0.138	-0.176	-1.029	-1.256	-0.089	0.226	-0.127	157
Wichita, KS MSA	589,195	4	54	-1.310	-1.087	-0.729	-0.119	-0.146	-2.265	-1.348	-0.177	0.327	-0.115	158
Beaumont-Port Arthur, TX MSA	378,477	7	60	-1.323	-1.370	-0.823	-0.062	-0.218	-1.388	-0.506	-0.177	0.420	-0.051	159
Killeen-Temple, TX MSA	358,316	7	32	-1.350	-1.254	-0.777	-0.213	-0.322	-1.981	-1.266	-0.261	0.298	-0.170	160
Albany-Schenectady-Troy, NY MSA	906,208	2	120	-1.360	-1.419	-0.234	-0.039	-0.082	-0.498	-0.287	-0.004	-0.027	-0.055	161
Appleton-Oshkosh-Neenah, WI MSA	385,264	3	79	-1.431	-1.356	-0.424	-0.104	-0.072	-0.650	-0.551	-0.069	0.101	-0.116	162
Lubbock, TX MSA	270,550	7	45	-1.444	-1.347	-0.787	-0.228	-0.106	-1.913	-1.407	-0.209	0.337	-0.223	163
Davenport-Moline-Rock Island, IA-IL MSA	362,790	4	28	-1.454	-1.349	-0.630	-0.130	0.070	-1.827	-1.205	-0.051	0.316	-0.165	164
Birmingham, AL MSA	997,770	6	148	-1.486	-1.191	-0.436	-0.079	-0.150	-0.747	-0.726	-0.113	0.123	-0.083	165
Saginaw-Bay City-Midland, MI MSA	390,032	3	41	-1.590	-1.518	-0.691	-0.130	-0.176	-0.391	-0.627	-0.036	0.387	-0.126	166
Toledo, OH MSA	631,275	3	107	-1.657	-1.457	-0.576	-0.104	-0.225	-1.276	-0.501	-0.010	0.283	-0.096	167
Scranton--Wilkes-Barre--Hazleton, PA MSA	614,565	2	27	-1.691	-1.581	-0.588	-0.184	-0.227	-0.361	-0.020	0.017	0.304	-0.169	168
Erie, PA MSA	280,291	2	29	-1.693	-1.787	-0.752	-0.196	-0.051	-1.371	1.067	-0.043	0.415	-0.210	169
Youngstown-Warren, OH MSA	554,614	3	49	-1.942	-1.748	-0.796	-0.176	-0.208	-0.982	-0.914	-0.040	0.436	-0.171	170
Evansville-Henderson, IN-KY MSA	305,455	3	33	-2.695	-2.664	-0.694	-0.136	-0.334	-2.039	-1.005	-0.071	0.245	-0.133	171
Census Divisions:														
New England	6,755,683	1	375	0.215	0.096	0.376	0.073	0.079	1.611	0.180	0.131	-0.227	0.058	3
Middle Atlantic	35,672,020	2	4,515	0.465	0.296	0.255	0.070	0.123	0.579	0.073	0.168	0.000	0.054	2
East North Central	32,786,507	3	8,405	-0.384	-0.449	-0.279	-0.036	-0.048	-0.549	-0.282	0.032	0.222	-0.033	6
West North Central	11,413,610	4	2,108	-0.653	-0.535	-0.349	-0.060	-0.084	-1.071	-0.891	0.026	0.232	-0.056	8
South Atlantic	40,292,714	5	19,366	0.041	0.097	-0.046	-0.031	-0.035	-0.019	0.185	-0.100	-0.029	-0.021	4
East South Central	8,457,649	6	1,416	-0.796	-0.730	-0.454	-0.113	-0.151	-0.769	-0.536	-0.136	0.184	-0.095	9
West South Central	24,734,026	7	4,730	-0.638	-0.596	-0.545	-0.068	-0.076	-0.981	-0.805	-0.163	0.265	-0.064	7
Mountain	15,381,913	8	14,471	0.035	0.115	-0.077	-0.042	-0.087	0.301	-0.054	-0.096	0.000	-0.022	5
Pacific	39,176,402	9	10,729	0.604	0.623	0.609	0.081	0.091	0.513	0.960	0.090	-0.407	0.072	1
Population Categories:														
Less than 500,000	57,630,737		3,597	-0.636	-0.607	-0.313	-0.084	-0.104	-0.355	-0.033	-0.060	0.114	-0.073	4
500,000 to 1,500,000	232,990,833		13,558	-0.539	-0.469	-0.229	-0.060	-0.071	-0.280	-0.180	-0.059	0.071	-0.055	3
1,500,000 to 5,000,000	491,452,831		31,981	0.108	0.120	0.063	0.011	0.006	0.090	0.165	0.005	-0.038	0.011	2
5,000,000+	298,945,500		15,945	0.691	0.545	0.310	0.077	0.112	0.185	0.003	0.103	-0.068	0.068	1

TABLE A2: SUMMARY STATISTICS FOR OBSERVED LAND SALES

Observations	68,757
Median Lot Size (Acres)	3.490
Mean Lot Size (Acres)	26.414
	(130.512)
Median Price Per Acre (Dollars)	272,838
Mean Price Per Acre (Dollars)	1,536,374
	(15,700,000)
No Proposed Use	15.9%
Proposed Use Commercial	0.3%
Proposed Use Industrial	7.5%
Proposed Use Retail	8.1%
Proposed Use Single Family	10.7%
Proposed Use MultiFamily	3.3%
Proposed Use Office	6.3%
Proposed Use Apartment	3.6%
Proposed Use Hold for Development	19.2%
Proposed Use Hold for Investment	4.3%
Proposed Use Mixed Use	1.7%
Proposed Use Medical	1.0%
Proposed Use Parking	0.9%
Mean Predicted Density (Housing Units/Sq. Mile)	1,334
	(2,918)
Sale in 2005	21.7%
Sale in 2006	20.5%
Sale in 2007	20.3%
Sale in 2008	15.6%
Sale in 2009	10.6%
Sale in 2010	11.4%

TABLE A3: DIFFERENT MEASURES OF THE LAND PRICE DIFFERENTIAL

Full Name	Total Land Sales	Residen-tial Land Sales	Land Diff. 1	Land Diff. 2	Land Diff. 3	Land Diff. 4	Land Diff. 5
New York, NY PMSA	1,603	1,603	3.291	1.551	1.525	1.902	0.810
San Francisco, CA PMSA	152	152	2.493	1.471	1.375	1.738	1.047
Jersey City, NJ PMSA	43	43	2.599	1.419	1.453	1.426	0.055
San Jose, CA PMSA	217	217	1.675	1.301	1.230	1.237	0.591
San Diego, CA MSA	957	957	0.944	0.862	0.835	1.017	0.469
Orange County, CA PMSA	233	233	1.874	1.177	1.137	1.000	0.282
Seattle-Bellevue-Everett, WA PMSA	1,626	1,626	1.194	0.840	0.820	0.935	0.127
Visalia-Tulare-Porterville, CA MSA	32	32	0.641	0.475	0.594	0.866	-0.202
Los Angeles-Long Beach, CA PMSA	1,760	1,760	1.661	0.945	0.916	0.864	0.015
Miami, FL PMSA	1,233	1,233	1.231	0.833	0.853	0.840	-0.208
Boston, MA-NH PMSA	122	122	0.730	0.639	0.659	0.784	-0.565
Newark, NJ PMSA	142	142	0.802	0.366	0.379	0.696	0.166
Washington, DC-MD-VA-WV PMSA	1,840	1,840	0.695	0.700	0.704	0.690	0.078
Fort Lauderdale, FL PMSA	741	741	1.112	0.773	0.766	0.661	-0.442
Oakland, CA PMSA	132	132	1.414	0.702	0.678	0.657	-0.173
Las Vegas, NV-AZ MSA	2,553	2,553	0.564	0.666	0.691	0.641	-0.075
Bergen-Passaic, NJ PMSA	79	79	1.255	0.670	0.687	0.582	
Nassau-Suffolk, NY PMSA	396	396	0.752	0.596	0.611	0.563	-0.240
Chicago, IL PMSA	3,511	3,511	-0.030	0.203	0.205	0.551	-0.063
Trenton, NJ PMSA	35	35	-0.134	0.578	0.577	0.538	
Madison, WI MSA	239	239	-0.243	-0.154	-0.200	0.501	-0.853
Ventura, CA PMSA	131	131	0.369	0.576	0.603	0.496	-0.457
Naples, FL MSA	78	78	0.423	0.525	0.506	0.475	-0.529
Philadelphia, PA-NJ PMSA	859	859	-0.173	0.085	0.098	0.378	-0.520
West Palm Beach-Boca Raton, FL MSA	321	321	1.170	0.410	0.413	0.332	-0.059
San Luis Obispo-Atascadero-Paso Robles, CA MSA	43	43	1.121	0.393	0.395	0.323	
Reno, NV MSA	57	57	-0.083	0.229	0.207	0.317	-0.609
Vallejo-Fairfield-Napa, CA PMSA	146	146	0.249	0.425	0.399	0.304	-0.597
Tacoma, WA PMSA	539	539	0.180	0.356	0.363	0.294	-0.396
Atlantic-Cape May, NJ PMSA	37	37	-0.003	-0.155	-0.196	0.289	-0.355
Sarasota-Bradenton, FL MSA	601	601	0.203	0.321	0.362	0.279	-0.312
Portland-Vancouver, OR-WA PMSA	1,191	1,191	0.325	0.290	0.303	0.253	-0.314
Orlando, FL MSA	1,612	1,612	-0.012	0.304	0.327	0.247	-0.616
Olympia, WA PMSA	250	250	-0.156	0.200	0.198	0.215	-0.518
Tampa-St. Petersburg-Clearwater, FL MSA	1,220	1,220	0.215	0.221	0.224	0.178	-0.730
Middlesex-Somerset-Hunterdon, NJ PMSA	101	101	-0.057	0.204	0.288	0.150	
Baltimore, MD PMSA	802	802	0.180	0.163	0.173	0.135	-0.442
Phoenix-Mesa, AZ MSA	5,946	5,946	-0.550	0.212	0.244	0.116	-0.721
Santa Rosa, CA PMSA	153	153	0.283	0.487	0.512	0.114	-0.201
New Haven-Meriden, CT PMSA	43	43	0.066	-0.199	-0.141	0.114	
Provo-Orem, UT MSA	47	47	0.282	0.258	0.237	0.083	-0.622
Melbourne-Titusville-Palm Bay, FL MSA	420	420	-0.221	0.039	0.055	0.047	-1.145
Denver, CO PMSA	2,015	2,015	0.098	-0.047	-0.065	0.029	-0.753
Salem, OR PMSA	54	54	-0.010	-0.264	-0.207	0.020	-0.867
Salt Lake City-Ogden, UT MSA	145	145	0.306	0.065	0.084	0.000	-1.093
Springfield, MA MSA	28	28	-0.388	-0.245	-0.223	-0.014	-0.407
Austin-San Marcos, TX MSA	384	384	-0.617	-0.293	-0.352	-0.015	-1.318
Allentown-Bethlehem-Easton, PA MSA	85	85	-0.566	0.023	0.066	-0.023	
Monmouth-Ocean, NJ PMSA	124	124	-0.128	0.015	0.045	-0.028	-0.460
Fort Myers-Cape Coral, FL MSA	294	294	0.053	0.113	0.132	-0.029	
Stockton-Lodi, CA MSA	163	163	-0.076	-0.002	0.062	-0.053	-0.806

TABLE A3: DIFFERENT MEASURES OF THE LAND PRICE DIFFERENTIAL

Full Name	Total Land Sales	Residen-tial Land Sales	Land Diff. 1	Land Diff. 2	Land Diff. 3	Land Diff. 4	Land Diff. 5
Wilmington-Newark, DE-MD PMSA	107	107	-0.482	-0.029	0.016	-0.071	
Jacksonville, FL MSA	793	793	-0.266	0.071	0.088	-0.092	-0.900
Nashville, TN MSA	455	455	-0.223	-0.159	-0.175	-0.098	-0.809
Riverside-San Bernardino, CA PMSA	2,452	2,452	-0.459	-0.020	-0.008	-0.105	-1.117
Minneapolis-St. Paul, MN-WI MSA	846	846	0.011	0.014	-0.009	-0.121	-1.302
Savannah, GA MSA	64	64	-0.711	-0.219	-0.178	-0.164	-1.105
Atlanta, GA MSA	5,229	5,229	-0.613	-0.187	-0.178	-0.186	-1.061
Fort Pierce-Port St. Lucie, FL MSA	71	71	-0.287	-0.084	-0.087	-0.196	-1.490
Raleigh-Durham-Chapel Hill, NC MSA	782	782	-0.397	-0.114	-0.128	-0.219	-1.179
Boulder-Longmont, CO PMSA	183	183	-0.139	-0.051	-0.070	-0.234	-1.126
Norfolk-Virginia Beach-Newport News, VA- MSA	392	392	-0.526	-0.174	-0.175	-0.235	-1.080
Myrtle Beach, SC MSA	84	84	-0.466	-0.628	-0.660	-0.264	
Lancaster, PA MSA	57	57	-0.910	-0.428	-0.413	-0.267	-0.962
Springfield, MO MSA	43	43	-0.821	-0.762	-0.715	-0.280	-1.878
Modesto, CA MSA	142	142	-0.208	-0.201	-0.174	-0.300	-0.709
Charleston-North Charleston, SC MSA	214	214	-0.366	-0.311	-0.330	-0.300	-1.099
Milwaukee-Waukesha, WI PMSA	399	399	-0.721	-0.451	-0.462	-0.329	-1.481
Eugene-Springfield, OR MSA	36	36	-0.110	-0.387	-0.279	-0.333	
Newburgh, NY-PA PMSA	54	54	-0.759	-0.117	-0.065	-0.341	-0.868
Lakeland-Winter Haven, FL MSA	561	561	-0.880	-0.198	-0.175	-0.375	-1.311
New Orleans, LA MSA	66	66	0.063	-0.279	-0.238	-0.377	-1.030
Albuquerque, NM MSA	114	114	0.192	-0.039	-0.016	-0.378	
Boise City, ID MSA	106	106	-0.400	-0.483	-0.505	-0.386	
Tucson, AZ MSA	1,749	1,749	-0.418	-0.319	-0.290	-0.400	-1.120
Worcester, MA-CT PMSA	56	56	-0.688	-0.395	-0.363	-0.404	
McAllen-Edinburg-Mission, TX MSA	61	61	-0.445	-0.375	-0.366	-0.414	
Kenosha, WI PMSA	58	58	-1.080	-0.130	-0.142	-0.418	
Daytona Beach, FL MSA	93	93	-0.135	-0.009	-0.047	-0.419	-0.702
Chattanooga, TN-GA MSA	51	51	-0.355	-0.425	-0.400	-0.424	
Colorado Springs, CO MSA	892	892	-0.059	-0.244	-0.258	-0.426	-0.957
Houston, TX PMSA	1,143	1,143	-0.514	-0.386	-0.400	-0.447	-1.106
Indianapolis, IN MSA	193	193	-0.787	-0.476	-0.463	-0.461	-1.547
Fayetteville-Springdale-Rogers, AR MSA	43	43	-0.267	-0.251	-0.312	-0.468	-1.464
Cincinnati, OH-KY-IN PMSA	637	637	-0.632	-0.434	-0.436	-0.476	-2.034
Dallas, TX PMSA	811	811	-0.451	-0.416	-0.442	-0.478	-1.287
Fresno, CA MSA	137	137	-1.030	-0.322	-0.326	-0.483	-0.729
Fort Collins-Loveland, CO MSA	344	344	-0.352	-0.291	-0.326	-0.485	-1.340
Hamilton-Middletown, OH PMSA	151	151	-0.731	-0.305	-0.317	-0.493	-2.006
Gary, IN PMSA	111	111	-0.598	-0.549	-0.528	-0.495	-2.323
Asheville, NC MSA	41	41	-0.472	-0.370	-0.348	-0.495	-2.044
Columbus, OH MSA	671	671	-0.716	-0.392	-0.395	-0.498	-1.307
Reading, PA MSA	36	36	-0.199	0.302	0.207	-0.504	-0.544
Merced, CA MSA	64	64	-0.948	-0.392	-0.387	-0.512	-0.493
Biloxi-Gulfport-Pascagoula, MS MSA	30	30	-1.183	-1.021	-0.925	-0.515	-2.251
Galveston-Texas City, TX PMSA	39	39	-1.051	-0.630	-0.632	-0.534	-1.490
Cleveland-Lorain-Elyria, OH PMSA	416	416	-0.649	-0.425	-0.415	-0.551	-2.162
Richmond-Petersburg, VA MSA	399	399	-0.774	-0.446	-0.446	-0.551	-1.068
Detroit, MI PMSA	679	679	-0.598	-0.528	-0.509	-0.554	-1.536
York, PA MSA	47	47	-0.800	-0.342	-0.395	-0.556	
Pittsburgh, PA MSA	240	240	-0.979	-0.723	-0.731	-0.557	-1.561
St. Louis, MO-IL MSA	364	364	-0.761	-0.612	-0.601	-0.573	-1.645

TABLE A3: DIFFERENT MEASURES OF THE LAND PRICE DIFFERENTIAL

Full Name	Total Land Sales	Residen-tial Land Sales	Land Diff. 1	Land Diff. 2	Land Diff. 3	Land Diff. 4	Land Diff. 5
Ann Arbor, MI PMSA	136	136	-1.412	-0.833	-0.828	-0.574	-2.509
Omaha, NE-IA MSA	118	118	-0.501	-0.591	-0.562	-0.631	-1.314
Greensboro--Winston Salem--High Point, NC MSA	438	438	-0.770	-0.463	-0.494	-0.633	-1.604
Tulsa, OK MSA	245	245	-0.489	-0.510	-0.540	-0.633	-2.141
Gainesville, FL MSA	34	34	0.121	-0.119	-0.159	-0.644	
Lincoln, NE MSA	24	24	0.013	-0.281	-0.171	-0.654	-1.543
Greeley, CO PMSA	320	320	-1.074	-0.372	-0.379	-0.676	-1.347
Hartford, CT MSA	101	101	-0.787	-0.729	-0.749	-0.680	-3.173
Spokane, WA MSA	55	55	-0.227	-0.591	-0.587	-0.695	-1.564
Brazoria, TX PMSA	62	62	-1.255	-0.845	-0.842	-0.716	
Canton-Massillon, OH MSA	40	40	-1.013	-0.844	-0.805	-0.719	
La Crosse, WI-MN MSA	21	21	-0.084	-0.462	-0.476	-0.732	-1.382
Harrisburg-Lebanon-Carlisle, PA MSA	89	89	-0.905	-0.551	-0.542	-0.757	-1.798
Louisville, KY-IN MSA	126	126	-0.626	-0.648	-0.634	-0.765	-1.830
Bryan-College Station, TX MSA	34	34	-0.781	-0.852	-0.815	-0.787	
Little Rock-North Little Rock, AR MSA	110	110	-0.791	-0.928	-0.921	-0.788	-2.032
Rockford, IL MSA	104	104	-1.733	-0.702	-0.667	-0.799	
Racine, WI PMSA	80	80	-1.226	-0.678	-0.685	-0.806	-1.612
Dayton-Springfield, OH MSA	116	116	-0.797	-0.709	-0.684	-0.809	-2.015
Amarillo, TX MSA	27	27	-1.110	-0.883	-0.846	-0.812	-2.648
Fort Worth-Arlington, TX PMSA	506	506	-0.528	-0.642	-0.653	-0.822	-1.612
Memphis, TN-AR-MS MSA	173	173	-0.812	-0.677	-0.689	-0.836	
Montgomery, AL MSA	33	33	-0.945	-1.345	-1.317	-0.839	
Baton Rouge, LA MSA	99	99	-0.522	-0.579	-0.606	-0.843	-2.338
Bakersfield, CA MSA	64	64	-0.874	-0.732	-0.661	-0.886	-2.442
Akron, OH PMSA	169	169	-1.122	-0.692	-0.667	-0.887	-1.489
Fort Wayne, IN MSA	39	39	-1.009	-0.641	-0.799	-0.889	-1.813
Jackson, MS MSA	43	43	-1.239	-0.867	-0.866	-0.902	
Columbia, SC MSA	139	139	-1.124	-1.126	-1.128	-0.914	
El Paso, TX MSA	94	94	-0.432	-0.768	-0.772	-0.925	-1.808
San Antonio, TX MSA	348	348	-0.908	-0.892	-0.897	-0.946	-1.965
Knoxville, TN MSA	193	193	-0.870	-0.758	-0.790	-0.960	
Hickory-Morganton-Lenoir, NC MSA	88	88	-1.475	-0.843	-0.810	-0.962	-2.493
Syracuse, NY MSA	65	65	-1.922	-1.419	-1.384	-0.977	-1.485
Kalamazoo-Battle Creek, MI MSA	31	31	-0.949	-1.071	-1.081	-0.980	
Augusta-Aiken, GA-SC MSA	66	66	-1.040	-0.986	-1.037	-0.992	-1.949
Green Bay, WI MSA	49	49	-0.721	-0.651	-0.668	-1.028	-1.521
Dutchess County, NY PMSA	33	33	-2.148	-0.809	-0.790	-1.041	-0.788
Lexington, KY MSA	29	29	-0.590	-0.854	-0.817	-1.057	
Greenville-Spartanburg-Anderson, SC MSA	507	507	-1.177	-0.984	-1.023	-1.067	-2.180
Brownsville-Harlingen-San Benito, TX MSA	52	52	-0.908	-1.056	-1.046	-1.069	-1.935
Kansas City, MO-KS MSA	477	477	-0.744	-0.716	-0.753	-1.103	-2.077
Des Moines, IA MSA	99	99	-1.020	-0.964	-0.954	-1.106	
Pensacola, FL MSA	102	102	-0.620	-1.010	-0.999	-1.122	-1.865
Lansing-East Lansing, MI MSA	40	40	-1.262	-1.188	-1.242	-1.124	-2.545
Oklahoma City, OK MSA	395	395	-0.900	-1.070	-1.042	-1.206	
Flint, MI PMSA	85	85	-1.504	-1.057	-1.088	-1.222	-2.119
Corpus Christi, TX MSA	74	74	-0.974	-1.134	-1.105	-1.229	-2.340
Grand Rapids-Muskegon-Holland, MI MSA	121	121	-1.097	-1.259	-1.219	-1.240	
Rochester, NY MSA	110	110	-2.365	-2.028	-1.960	-1.279	-3.469
Buffalo-Niagara Falls, NY MSA	104	104	-1.073	-1.114	-1.143	-1.286	-1.632

TABLE A3: DIFFERENT MEASURES OF THE LAND PRICE DIFFERENTIAL

Full Name	Total Land Sales	Residen-tial Land Sales	Land Diff. 1	Land Diff. 2	Land Diff. 3	Land Diff. 4	Land Diff. 5
Portland, ME MSA	25	25	-1.788	-1.454	-1.401	-1.293	
Mobile, AL MSA	135	135	-1.282	-1.207	-1.165	-1.293	-2.462
Duluth-Superior, MN-WI MSA	22	22	-0.344	-1.104	-1.119	-1.296	
Cedar Rapids, IA MSA	33	33	-1.194	-1.247	-1.129	-1.301	-1.911
Wichita, KS MSA	54	54	-0.881	-1.170	-1.087	-1.310	-2.121
Beaumont-Port Arthur, TX MSA	60	60	-1.387	-1.387	-1.370	-1.323	-2.372
Killeen-Temple, TX MSA	32	32	-1.097	-1.267	-1.254	-1.350	
Albany-Schenectady-Troy, NY MSA	120	120	-1.626	-1.411	-1.419	-1.360	-2.450
Appleton-Oshkosh-Neenah, WI MSA	79	79	-1.613	-1.313	-1.356	-1.431	-2.246
Lubbock, TX MSA	45	45	-1.258	-1.401	-1.347	-1.444	
Davenport-Moline-Rock Island, IA-IL MSA	28	28	-1.133	-1.382	-1.349	-1.454	-1.503
Birmingham, AL MSA	148	148	-1.048	-1.209	-1.191	-1.486	
Saginaw-Bay City-Midland, MI MSA	41	41	-1.752	-1.530	-1.518	-1.590	-2.019
Toledo, OH MSA	107	107	-1.541	-1.450	-1.457	-1.657	
Scranton--Wilkes-Barre--Hazleton, PA MSA	27	27	-2.073	-1.689	-1.581	-1.691	-3.245
Erie, PA MSA	29	29	-1.491	-1.892	-1.787	-1.693	
Youngstown-Warren, OH MSA	49	49	-1.972	-1.745	-1.748	-1.942	
Evansville-Henderson, IN-KY MSA	33	33	-1.999	-2.913	-2.664	-2.695	

Land-value data from CoStar COMPS database for years 2005 to 2010. Land value differentials 1 through 4 for each MSA correspond to the specifications in Table 1; differential 5 is the same as differential 4 but for residential land only.

TABLE A4: REVERSE REGRESSION OF LAND VALUES ON HOUSING COSTS

Specification	Cobb-Douglas Land Only	Cobb-Douglas Const Cost
Housing-Cost Measure	Average	Average
	(1)	(2)
Land-Value Differential	1.346	1.438
	(0.163)	(0.139)
Construction-Cost Differential		-0.326
		(0.439)
Geographic Constraint Index: z-score	0.002	0.021
	(0.051)	(0.044)
Regulatory Index: z-score	0.003	All
	(0.048)	Subindices
Constant	0.000	-0.001
	(0.043)	(0.039)
Number of Observations	688	668
Adjusted R-squared	0.647	0.661
Implied Land-Cost Share	0.743	0.695
	(0.090)	(0.067)
Implied Material-Cost Share		0.227
		(0.297)

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 1; constituent components of Wharton Residential Land Use Regulatory Index (WRLURI) from Gyourko et al (2008).

TABLE A6: MODEL OF HOUSING-COST DETERMINATION WITH ALTERNATIVE MEASURES OF LAND VALUES

Specification Dependent Variable	Restricted Translog Residential Land Only Hous. Price (1)	Restricted Translog Raw Land Differentials Hous. Price (2)	Restricted Translog Residential Land Only Hous. Price (3)	Restricted Translog Raw Land Differentials Hous. Price (4)
Land-Value Differential	0.282 (0.025)	0.231 (0.015)	0.255 (0.024)	0.215 (0.014)
Construction-Cost Differential	0.718 (0.025)	0.769 (0.015)		
Construction-Wage Differential			0.745 (0.024)	0.785 (0.014)
Land-Value Differential Squared	0.083 (.013)	-0.005 (.018)	0.075 (.013)	0.005 (.016)
Construction-Cost Differential Squared	0.083 (.013)	-0.005 (.018)		
Construction-Wage Differential Squared			0.075 (.013)	0.005 (.016)
Land-Value Differential X Construction-Cost Differential	-0.166 (.026)	0.010 (.036)		
Land-Value Differential X Construction-Wage Differential			-0.150 (.026)	-0.010 (.032)
Geographic Constraint Index: z-score	0.137 (0.014)	0.105 (0.013)	0.160 (0.013)	0.126 (0.012)
Regulatory Index: z-score	0.107 (0.010)	0.100 (0.008)	0.102 (0.010)	0.095 (0.008)
Constant	0.189 (0.021)	0.004 (0.012)	0.170 (0.019)	-0.002 (0.011)
Number of Observations	593	668	609	688
Adjusted R-squared	0.783	0.832	0.782	0.833
Elasticity of Subsitution	0.590 (0.046)	1.030 (0.214)	0.608 (0.044)	0.971 (0.186)

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 2. Residential Land includes only those sales with a proposed use of Single Family, MultiFamily, or Apartments. Raw Land differentials are the land value differentials obtained by regressing log price per acre on a set of MSA dummies with no other covariates.

TABLE A7: INSTRUMENTAL VARIABLES ESTIMATES

Dependent Variable	Land Rent (1)	Land Rent minus Construction Costs (2)	Land Rent (3)	Land Rent minus Construction Wages (4)
Panel A: First Stage				
Construction-Cost Differential	3.582			
	(0.312)			
Construction-Wage Differential			1.547	
			(0.287)	
Geographic Constraint Index: z-score	0.100	0.254	0.280	0.290
	(0.052)	(0.065)	(0.061)	(0.065)
Regulatory Index: z-score	0.100	0.206	0.146	0.183
	(0.052)	(0.056)	(0.063)	(0.060)
Average Winter Temperature: z-score	0.290	0.106	0.065	0.054
	(0.046)	(0.060)	(0.057)	(0.061)
Constant	-0.281	-0.282	-0.277	-0.280
	(0.045)	(0.053)	(0.050)	(0.053)
F-statistic	88.582	39.745	44.391	41.249
Specification	Cobb-Douglas	Restricted Cobb-Douglas	Cobb-Douglas	Restricted Cobb-Douglas
Dependent Variable	House Price	House Price	House Price	House Price
Panel B: Second Stage				
Land-Value Differential	0.547	0.615	0.281	0.202
	(0.172)	(0.397)	(0.532)	(0.617)
Construction-Cost Differential	0.352	0.385		
	(0.492)	(0.397)		
Construction-Wage Differential			0.933	0.798
			(0.744)	(0.617)
Geographic Constraint Index: z-score	0.069	0.046	0.154	0.181
	(0.053)	(0.120)	(0.155)	(0.180)
Regulatory Index: z-score	0.050	0.032	0.069	0.098
	(0.034)	(0.079)	(0.085)	(0.110)
Constant	0.153	0.172	0.080	0.057
	(0.073)	(0.121)	(0.164)	(0.189)
Number of Observations	165	165	171	171
Adjusted R-squared	0.703	0.511	0.791	0.687
Land-Value Differential from OLS Regression	0.269	0.286	0.290	0.296
	(0.051)	(0.052)	(0.044)	(0.044)
p-value from Chi-squared test of regressor endogeneity	0.068	0.328	0.987	0.879

Robust standard errors, clustered by CMSA, in parentheses. Specifications in columns 1 and 2 correspond to specifications 1 and 2 from table 4A, respectively; specifications in columns 3 and 4 correspond to specifications 1 and 2 from table 4B, respectively. Data sources as described in Table 2, except Average Winter Temperature, which is taken from Albouy et al. (2011).