Metropolitan Land Values and Housing Productivity*

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PRELIMINARY: PLEASE DO NOT CITE WITHOUT AUTHORS' PERMISSION.

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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, 30 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 0.5. 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 occupies the largest share of household expenditure of all consumption goods, and its value depends fundamentally on the land upon which it is built. Land values are extremely heterogenous, reflecting land's scarcity, its opportunities for development, and the value of the amenities it provides to households and firms. 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 for American metropolitan areas, using recent data from CoStar, a commercial real estate company.

Together with data on housing values, these data allow us to estimate the cost relationship between housing and land, as well as non-land costs and, perhaps most interestingly, artificial and natural constraints to development due to regulation and geography. We find that on average, 30 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 into housing production of around 0.5. Consistent estimation of these parameters requires controlling for regulatory and geographic constraints, which increase the cost of housing significantly relative to land.

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 value of housing predicted by land and other costs, and its actual value. The housing productivity measure provides the most important indicator of a city's productivity in the non-tradeables sector, and can be contrasted with measures of productivity in the tradeables sector. Contrary to assumptions sometimes in the literature that the two are the same (e.g. Shapiro 2006 and Rappaport 2007), we find that the two are negatively related, with productivity in tradeables increasing in city size but productivity in housing decreasing in city size. Yet, we find that lower housing productivity, including that due to land-use regulation, is associated with a higher quality of life across cities.

Most measures of land values rely on a residual method that subtracts an estimated value of the structure from the observed measure of an entire property's value, to infer the value of land. Davis and Palumbo (2007) employ this 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, attributing such costs to the value of land. From our analysis this explains why Davis and Palumbo find the average cost-share of land in housing to have risen to an unprecedented number of almost 50 percent.

Ihlanfeldt (2007) takes direct measures of 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 look at the relationship between housing costs and land values or regulations. Glaeser et al. (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 entail the use of any additional land, obviating the need for land price data.

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 taken in Epple et al. (2010), who use separately assessed land and structure values for every house in Alleghany County, Pennsylvania, where they find a cost of land of 14 percent. Our estimates are based on metropolitan level-indices that must take into account differences in construction costs and a much wider away of regulatory differences.[1]

We estimate the elasticity of substitution between land and other factors of production to be between 0.32 and 0.5 in our baseline translog estimates, but we cannot formally reject the hypothesis that the elasticity of substitution equals one, or equivalently that the production function is Cobb-Douglas. Historically, most estimates of the elasticity of substitution have been below one, for instance see McDonald (1981) for a survey of the older literature. More recent research has

[1] 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.

found somewhat higher values: Thorsnes (1997) finds values between 0.81 and 1.08; Epple et al. (2010) find estimates between 1 and 1.16, and are also unable to reject the null hypothesis of a Cobb-Douglas production function.

2 Model of Land Values and Housing Production

We base propose a basic cost-function approach to housing, 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.

2.1 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. Land is paid a city-specific price r_j, while materials are paid price v_j. In our empirical work we will operationalize M as the installed structure component of housing, so the price v_j is conceptualized as total construction costs, possibly an aggregate of local labor and tradeable goods. Unit cost in the housing sector is $c^Y(r_j, v_j; A_j^Y) \equiv \min_{L,M}\{r_jL + v_jM : F_Y(L, M; A_j^Y) = 1\}$.

Assuming the housing market is perfectly competitive, then in equilibrium housing prices must be equal to marginal costs:

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

This equation can be 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 $\bar{A}^Y = \bar{p}/\partial c^Y(\bar{r}, \bar{m}, \bar{A}^Y)/\partial A$. Rearranged, this equation measures unobserved local home-productivity,

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

from how high land and material costs are relative to housing costs, $\hat{p}^j$. In other words, cities are inferred to have low housing productivity if the housing price of houses is high relative to local input costs.

If we assume that 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, $(\hat{r}_j - \hat{v}_j)^2$. [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 when $\sigma^Y < 1$.

[2]On the other hand, if housing productivity is embodied in land, i.e., $F^Y(L, M; A_j^Y) = F^Y(A_j^Y L, M; 1)$, then

$$\hat{p}_j = \phi^L \hat{r}_j + (1-\phi^L)\hat{m}_j + \frac{1}{2}\phi^L(1-\phi^L)(1-\sigma^Y)(\hat{r}_j - \hat{m}_j - \hat{A}_j^Y)^2 - \phi^L \hat{A}_j^Y \tag{6}$$

A symmetric condition would hold if housing productivity is instead embodied in non-land inputs.

2.2 Empirical Model

We model housing costs empirically using the translog cost function of Christensen et al. (1973):

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

where Z^j is a vector of city attributes that impact housing productivity, such that

$$\hat{A}_Y^j = Z^j(-\gamma) + \hat{A}_Y^{0j} \tag{8}$$

and $\hat{A}_Y^{0j} = -\varepsilon_j$ is the residual component of housing productivity.[3] CRS imply the three restrictions

$$\beta_1 = 1 - \beta_2 \tag{9a}$$

$$\beta_3 = \beta_4 = -\beta_5/2 \tag{9b}$$

in which case $\phi^L = \beta_1$and, with factor-neutral productivity, $\sigma^Y = 1 - 2\beta_3/\left[\beta_1(1-\beta_1)\right]$. Cobb-Douglas production technology, imposes the restriction $\sigma^Y = 1$, which in equation (7) amounts to the three restrictions:

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

2.3 Full Determination of Land Values

The full determination of land values requires filling out a model for location demand based on amenities to individuals, bundled in terms of quality of life, Q_j, and to firms and tradeable sector, bundled as trade productivity, A_j^X.

To perform this exercise, we allow there to be two types of individuals, $k = X, Y$, where type-Y individuals work in the housing sector. Preferences are modeled by $U^k(x, y; Q_j^k)$, which

[3] Non-neutral productivity differences would suggest inteacting productivity shifters Z_j with input prices $\hat{r}_j$ and $\hat{m}_j$ in equation (7). Estimated coefficientes on these estimates were generally not found to be statistically significant in most specifications.

is quasi-concave over x and y, and increasing in Q_j^k, which 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 makes up a fraction, s_w, of total income m_j^k, the rest of which is independent of location, and 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

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

where Q_j^k is normalized so that $\bar{Q}^k = 1/\partial e^k(\bar{p}, \bar{u}^k, \bar{Q}^k)/\partial A$, s_y^k is the average expenditure share on housing, and τ^k is the average marginal tax rate for type k. 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 $s_y \equiv \mu^X s_y^X + \mu^Y s_y^Y$, $\tau \equiv \mu^X \tau^X + \mu^Y \tau^Y$, and $s_y \equiv \mu^X \hat{w}_y^X + \mu^Y \hat{w}_y^Y$.

The productivity of firms in the tradeable sector is modeled similarly to the housing sector except that the price of output is uniform across cities and output is modeled through the CRS and CD production 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 that for (3) yields the following 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-share of land and labor in production. Note that land is paid price the same 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 $\phi^N = \varpi^L(1-\phi^L)$, then 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) we get that the land-value differential, times the the average income share of land, s_R, is equal to the total productivity differential plus the quality-of-life differential, minus a tax differential to the government that depends on wages:

$$s_R \hat{r}_j = \hat{A}_j + \hat{Q}_j - \tau s_w \hat{w}_j \tag{16}$$

3 Data

We calculate our land price index from the CoStar COMPS database of commercial real estate sales, while we calculate house price and wage differentials across cities using data from the 2006-2008 American Community Survey 3 percent sample. Additionally, we use various indices of housing market conditions across U.S. cities, including the Wharton Residential Land Use Regulatory Index (WRLURI), an index of topographical constraints to residential development calculated by Saiz (2010), and an index of construction costs across cities published by the Robert Snow Means company (RS Means index).

The CoStar Group is an industry-leading provider of commercial real estate information. It claims to have the industry's largest research organization and estimates that its researchers make more than 10,000 calls a day to commercial real estate professionals. The CoStar COMPS database includes transaction details for all types of commercial real estate, including Office, Industrial, Retail, and Land. In this study, we take as our initial data set every commercial land sale in the COMPS database through the second quarter of 2010, which we downloaded during the period of June 28th through June 30th, 2010 and on September 7th, 2010. After dropping observations without complete information for lot size, sales price, county, and date, we are left with 31,252. observations used in our land price estimation.[4]

Summary statistics for our sample of land sales are shown in Table A2. We observe land sales in 310 Metropolitan Statistical Areas and Primary Metropolitan Statistical Areas.[5] The median price per acre in our sample was $220,223 while the mean was $933,689; the median lot size was 3.0 acres while the mean was 26.2. We controlled for 12 categories of "proposed use" for each property in addition to a category for no proposed use. Approximately 19.8% 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 (a property could have more than one proposed use). As an additional control, we used the Google Maps automated programming interface to calculate the driving distance and driving time between each property and the center of the MSA or PMSA (as defined by Google Maps). 22,350 properties had an address recognized by Google Maps. For these properties, the mean driving distance from the city center was 37,110 meters (23.1 miles) and the mean driving time was 1,867 seconds (31.1 minutes). We calculate a land price index for each city by regressing the log price per acre of each sale on a set of dummy variables for each MSA or PMSA, a set of dummies for quarter of sale, a set of dummies for planned use, and log lot size. In an alternative specification, we include log driving distance and log driving time from the city center as controls. 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 land value regressions, shown in Table A3, are discussed in the next section.

[4]The data cleaning also involves dropping 3,155 observations that are not in a metropolitan area, 116 observations prior to 2005, 5 observations from the third quarter of 2010, and 6 observations with a listed lot size of zero acres leaves us with 31,327 observations. We also drop 58 observations with a reported price per acre less than $100 and 17 observations with more than 5,000 acres.

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

We calculate wage and house price differentials using the 2006-2008 American Community Survey 3% sample, using a methods detailed in the appendix. The spirit of the exercise is to regress wages and housing costs on a rich set of observable characteristics, including a set of dummies for metro area. We then take the coefficients on the metro area dummies as our indices of wages and housing costs across metro areas.

The Wharton Residential Land Use Regulatory Index (WRLURI), described in Gyourko et al. (2008), is based on survey responses from municipal planning officials regarding the regulatory process. The WRLURI is constructed by factor analysis of 11 constituent subindices, which we also use in our analysis: 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). Thus, two of the subindices concern state level behavior while nine are local in nature. The local assembly index measures whether zoning requests must be approved at a town meeting, a feature unique to New England; all other subindices are national in scope. The components of the WRLURI generally have positive correlations with one another but this is not always the case; for instance, the SCII is negatively correlated with five of the other subindices. The WRLURI and subindices are constructed so that a higher score corresponds to an increase in regulatory stringency.

The index of topographic constraints to residential development is described by Saiz (2010), who uses satellite imagery to calculate land scarcity in metropolitan areas. The index measures the fraction of undevelopable land within a 50 km radius of the city center, where land is undevelopable if it is covered by water or wetlands, or has a slope of 15 degrees or steeper, which effectively inhibits development.

We re-normalize both the WRLURI and Saiz indices to have mean zero and standard deviation one, weighted by population in our sample. Therefore, both the WRLURI and the Saiz index can be interpreted as z-scores in our analysis. Saiz (2010) shows that his index of topographic constraints is positively correlated with regulatory constraints as measured by the WRLURI. This result holds in our sample of metropolitan areas as well: a regression of the WRLURI on the Saiz index gives a coefficient of 0.302 (s.e. = 0.080).

The RS Means company has published its Building Construction Cost Data for 68 years, and its multi-city construction cost index is widely used in the literature (e.g. Davis and Palumbo (2007), Glaeser et al. (2005b)). For each city in the index, RS Means reports construction costs for a composite of nine common structure types. The index for each city is reported proportionally to the national average, which is normalized to 100. The index is meant to include the costs of labor, materials, and equipment rental. It does not include cost variations due to regulatory restrictions, restrictive union practices, or regional differences in building codes. 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. The RS Means construction cost index includes data for 159 of the 165 cities we use in our analysis.

Although there are 311 MSAs and PMSAs represented in our database of land sales, we restrict our analysis to areas for which we observe least 20 land sales, that are identifiable in the ACS, and that are present in the WRLURI and Saiz index data sets, leaving 165 MSAs and PMSAs, for which we have 29,602 land sale observations, 7.5 million wage observations, 339,524 of which are in the construction sector, and 5.5 million housing cost observations. To assist in interpretation of 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 percent deviation of the price of each variable in a given city from the national average.

In portions of our analysis we use MSA population and weighted population density. For population, we use the 2009 Census estimates. To calculate weighted population density, we calculate the population density of each census tract in a PUMA to calculate the population-weighted density at the PUMA level. We then weight by PUMA level population to get the weighted population density for each MSA or PMSA.

4 Results

The main measures for the analysis are reported in table 1 for a selected number of metropolitan areas, ranked by land value, and by metropolitan size. The highest land values in the sample are in San Jose and New York. In general, large coastal cities have the highest land values and housing costs, while smaller cities in the South and Midwest have lower values. The lowest values are in Michigan and upstate New York.

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 constraints. We take a brief look at the reverse regression of land values on housing costs and other variables.

4.1 Simple Model with Constraints

The land-value and housing-cost indices are plotted in figure 1A. A simple linear regression produces a slope of 0.49, which, assuming all other costs are uniform across cities, is land's estimated share of costs. The curvature in the quadratic regression yields an estimate of the elasticity of substitution of 0.25, which is significantly different from one, the CD case, and implies a wide range of cost shares across metro areas from 0.24 to 0.82. A visual representation of a city's housing productivity is given by the vertical distance below the regression line: thus, San Francisco ("SF") has low housing productivity and Las Vegas ("LAS") has high housing productivity. The curves here represent estimates from the data with no controls and will change as other variables are added to the model. Figure 1B plots the land-value and housing-cost indices, controlling for distance from the city center. The estimates using this data yield slightly lower land-cost shares, although the differences are not significant.

The results in columns 1, 2, and 5 of table 2 reveal that controlling for regulatory and geographic constraints lowers the estimated cost-share of land to 0.36, and leaves the elasticity of substitution unchanged. Moreover, a standard deviation increase in either the geographic constraint or regulatory index predicts a 7 to 8 percent increase in housing costs. These simple indices account for substantial variation in housing costs across metro areas. Column 3 presents results using a housing-cost measure based only on gross rents; the lower estimates suggest that housing rents are less responsive to differences in land values and constraints. The results in column 4 show the opposite holds true of estimates using housing-cost measures based on the value of owner-occupied housing alone.[6] Because it is not clear that one measure is necessarily more accurate and the share of renters varies substantially across metro areas, we proceed with our original housing-cost measure, bearing in mind these effects.

4.2 Non-Land Input Cost Differences

Measures of construction costs and of construction wages are plotted against land values in figures 2A and 2B. We see that both measures of non-land input costs are strongly correlated with land values, implying that accurate estimation must control for these costs.[7] The figures also plot estimated zero-profit conditions (ZPCs) for firms, derived from equation 5 estimated without controls, for fixed values of housing costs and productivity, $\hat{p}_j + \hat{A}_j^Y$. The slope of the ZPC is the ratio of land costs to non-land costs, $-\phi_j^L/(1-\phi_j^L)$. In the CD case the slope of the ZPC is constant. With the estimated elasticity, σ^Y, of less than one, the slope of the ZPC increases with land values,

[6] 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 1.79-percent increase in housing values, or a 1.53-percent increase in the housing-cost measure. Jointly, a one-percent increase in rents (values) increases the housing-cost index by 0.34-percent (0.66-percent).

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

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 2C, 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 3A presents estimates using the RS Means construction costs. Columns 1 and 2 use the CD specification while columns 3 and 4 use the translog specification; columns 2 and 4 impose the CRS restrictions. Both the CD and CRS restrictions pass at usual statistical sizes. Thus, the CD formulation in column 2 appears plausible. Yet the point estimate of σ^Y implied by the estimates in column 4 is appreciably lower than one at 0.5, and is quite consistent with estimates from the literature. In this specification we find a cost-share of land of 33 percent and a somewhat smaller impact of the geographic and regulatory constraints, as both are positively correlated with construction costs.

Results in columns 1 through 4 of table 3B, which uses construction wages, rather than costs, are quite similar except that they are more prone to reject the CD restriction, with a slightly lower point estimate for σ^Y of 0.41. The estimates in column 5 imply that a 1-percent increase in construction wages predicts a 0.75 percent increase in construction costs, which appear unrelated to land costs and geographic constraints, but may be increased slightly by regulation. 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 17 percent.

4.3 Disaggregating the Regulatory Index

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 4, ordered according to the size of its 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 are different.

In columns 2 and 3 we report our favored estimates, using the CRS specifications from column 4 of table 3, but with the disaggregated regulatory subindices. The number of subindices relative to the number of observations lowers the power of this exercise, as does the multiple hypothesis testing, although they significantly improve the explanatory power of the empirical model. The results are intriguing as the subindices that appear to increase housing costs the most are typically not those with the highest factor loading. Here we find exactions, supply restrictions, and political and court involvement at the state level to be the most strongly related to high housing costs. Two results that are difficult to explain are that requirements for open space and density restrictions appear to lower housing costs: these could be the result of true economic processes or of endogenous regulatory processes that are not modeled. In addition we find that the cost-share of land appears to be very close to 30 percent and that the elasticity of substitution is between 0.32 and 0.46. These estimates predict the cost share of land in the sample ranges between 13 and 52 percent.

4.4 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 5, suggest a somewhat larger share of land costs relative to non-land costs.[8]

[8] An explanation of measurment error will soon be here.

4.5 Productivity in Housing and Tradeables

In table 6 we provide measures of housing productivity using the empirical model in column 3 of table 4, where $\hat{A}^Y_j = Z_j(-\gamma^*) - \varepsilon^*_j$, 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 $\hat{A}^X_j$ and overall quality-of-life $\hat{Q}_j$.[9] Productivity in the housing and tradeable sectors are plotted against each other in figure 3, where they are strongly negatively correlated: on average a 1-percent increase in trade productivity predicts a 0.84-percent decrease in trade productivity.

This could be the result of increasing returns to scale at the city level in the tradeable sector being offset by decreasing returns to scale at the city level in the housing sector, as agglomeration economies in tradeables are offset by agglomeration diseconomies in non-tradeables. This hypothesis is explored in table 7, which examines the relationship of productivity with population levels (at the Consolidated MSA 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 roughly as large as the positive relationships with trade productivity in column 1. Much of this appears to be the result of endogenous regulatory behavior increasing in larger, denser cities: taking out the component of housing productivity due to the regulatory subindices in column 3, the relationship is much weaker. 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

[9]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.

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.

Figure 4 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 actually slightly larger, 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 almost exactly in this range at about 22 percent.

Other explanations for this phenomenon are easily possible. 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 most convincing empirical model from this analysis suggest that the average cost share of land in metropolitan areas is about 30 percent. Without controls for building costs and geographic and regulatory constraints, this share may be overestimated. Because substitution possibilities appear to be limited between land and other factors, with an estimated elasticity around 0.4, this share ranges from 13 to 52 percent. 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 about 7 percent of income.

Housing productivity varies considerably across metro areas with a standard deviation of 0.16 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, exactions, supply restrictions, and state court and 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 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. 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.

Figure 1A: Housing Costs vs. Land Values

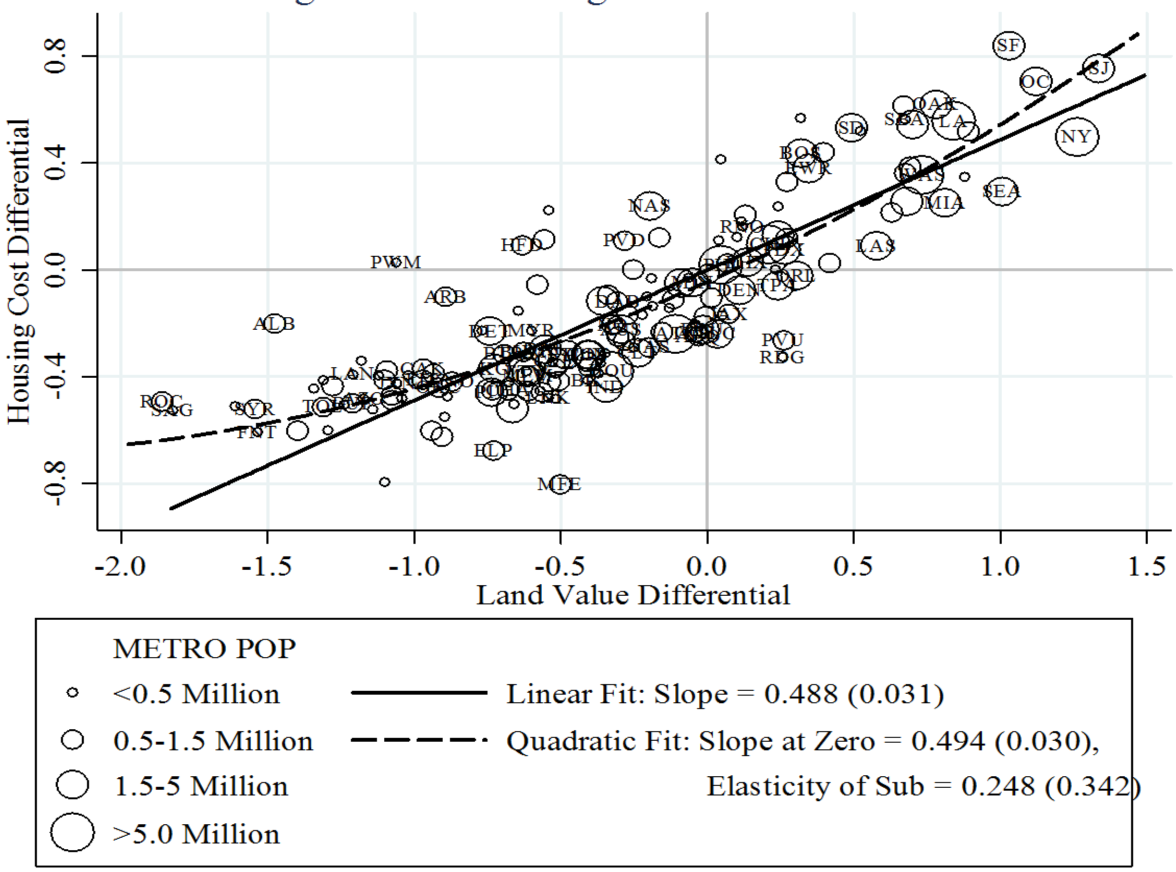

Figure 1B: Distance-Adjusted Housing Costs vs. Land Values

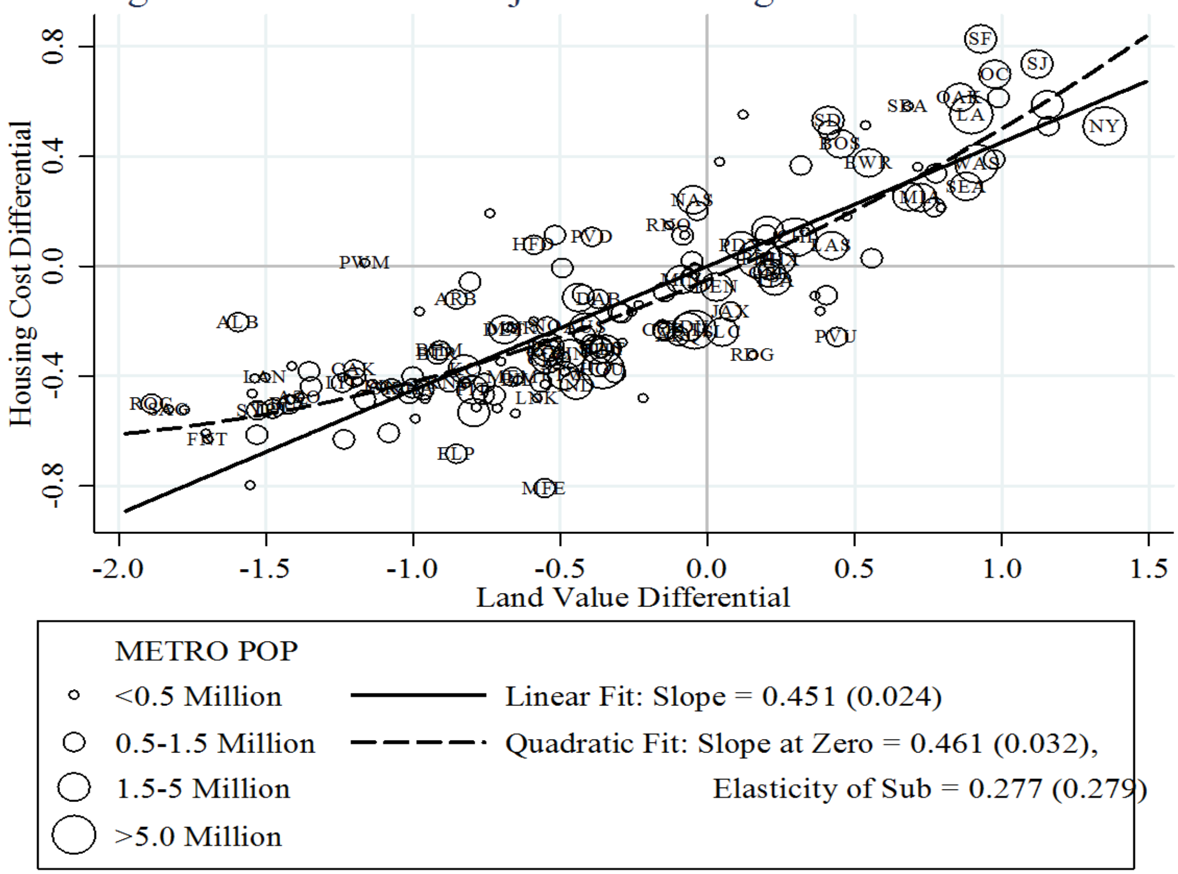

Figure 2A: Construction Costs vs. Land Values

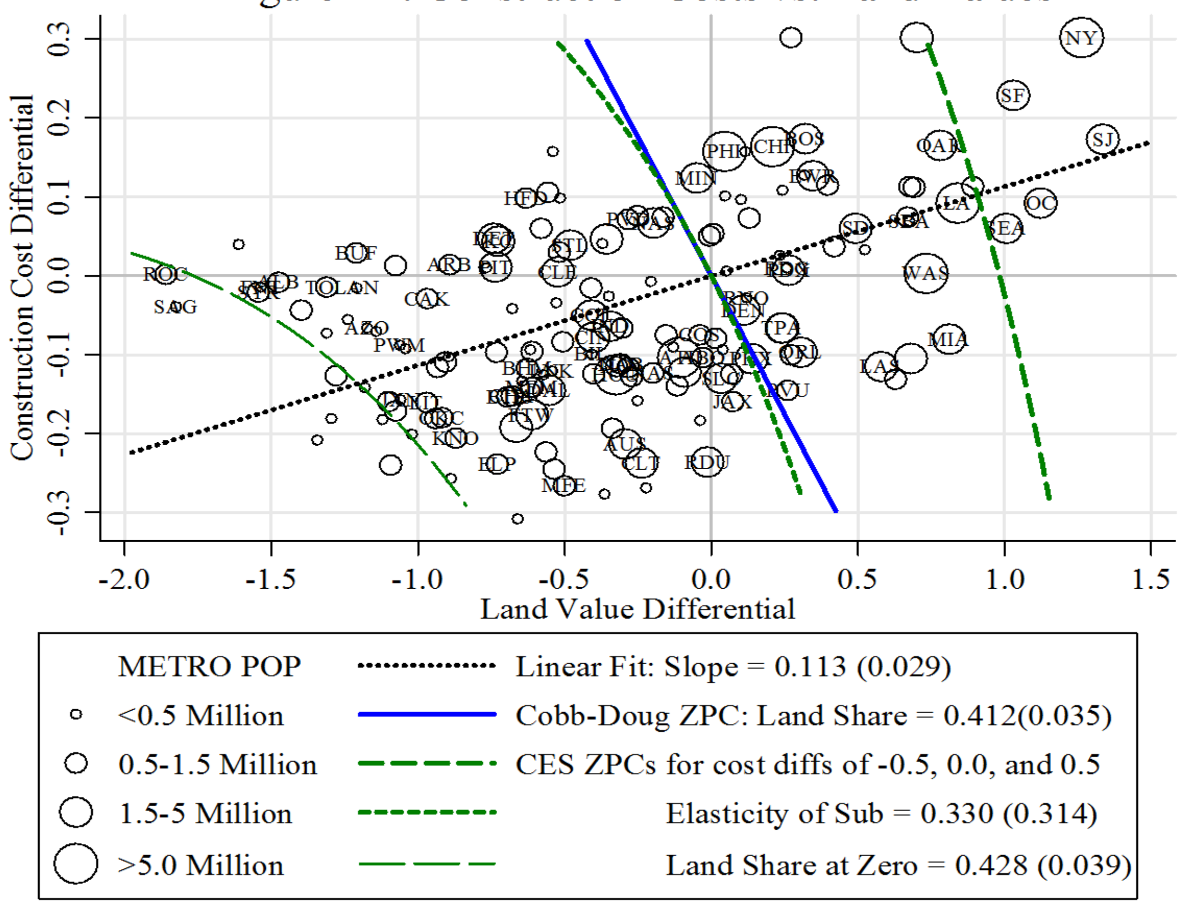

Figure 2B: Construction Wages vs. Land Values

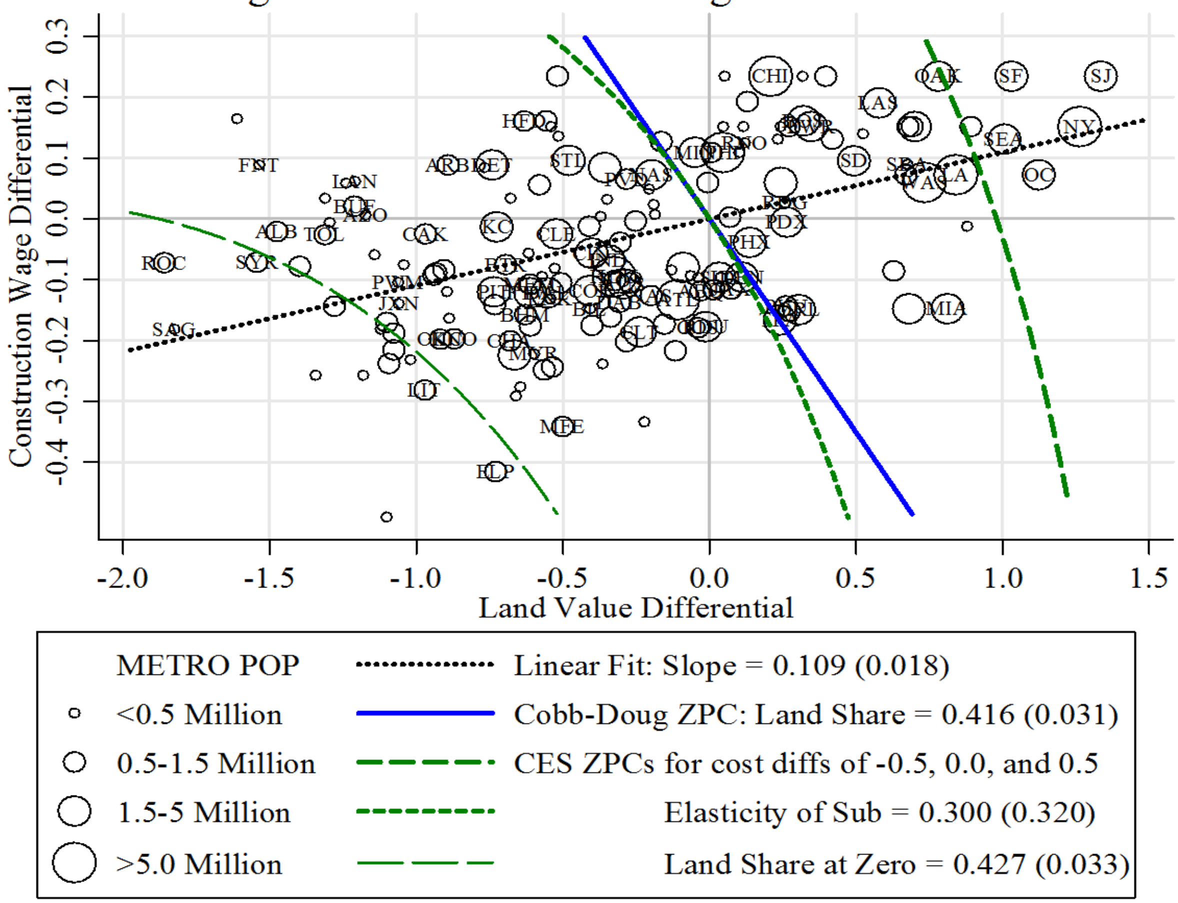

Figure 2C: Plot of housing costs predicted using data and basic model in 2A

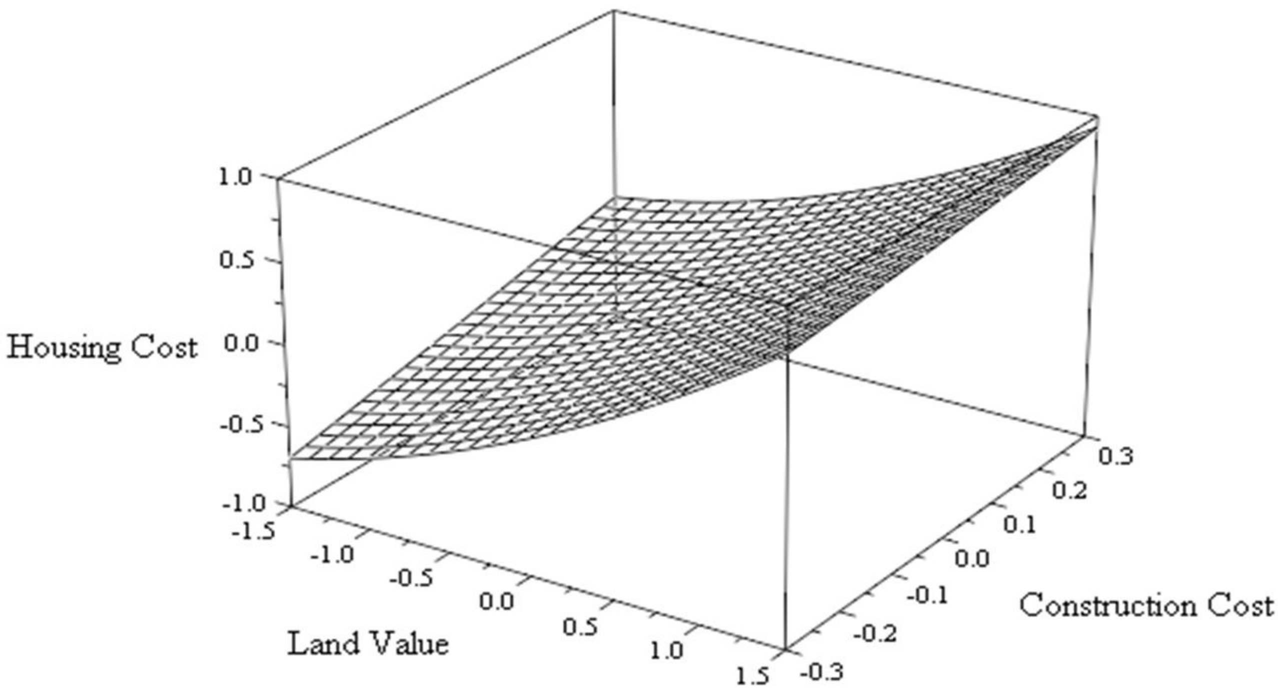

Figure 3: Productivity in the Tradeable and Housing Sectors

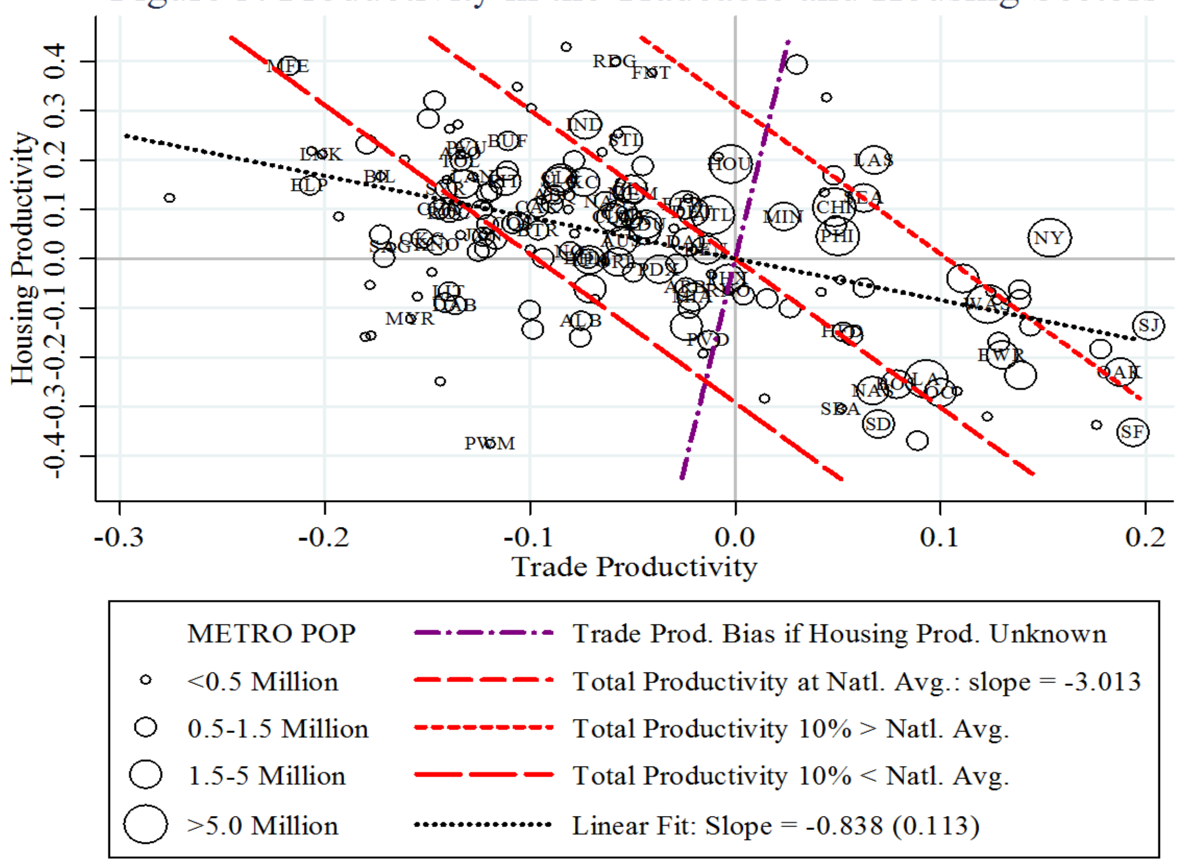

Figure 4: Quality of Life vs. Housing Productivity

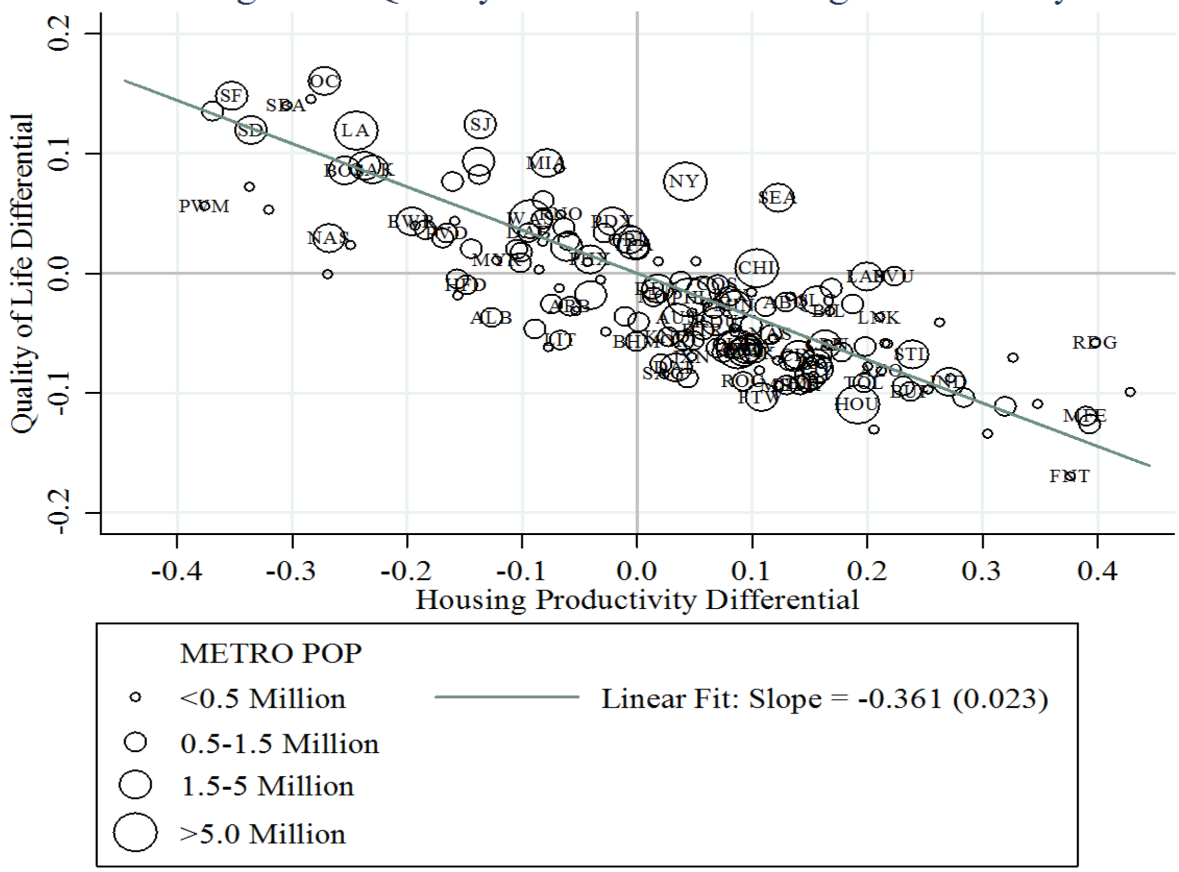

Figure A: Construction Costs vs. Construction Wages

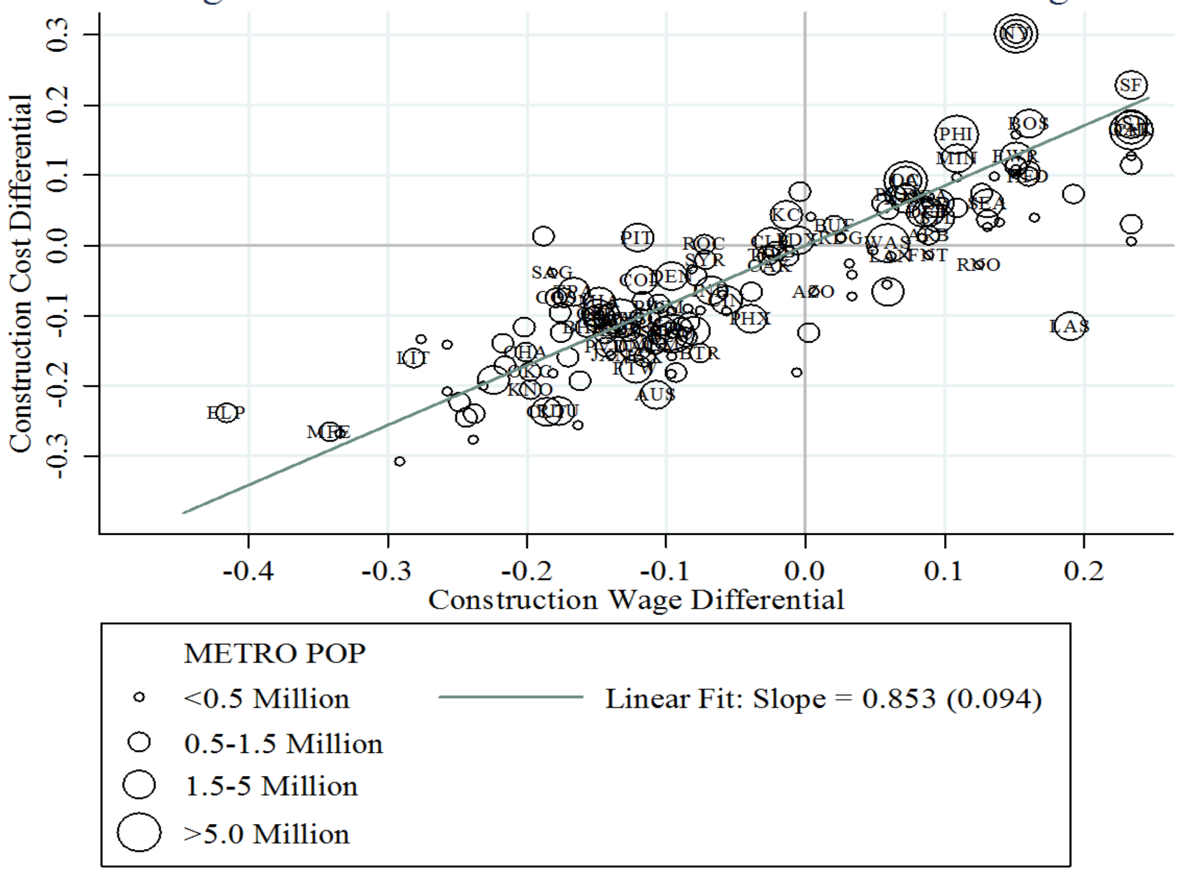

Figure B: Construction Wages vs. Overall Wages

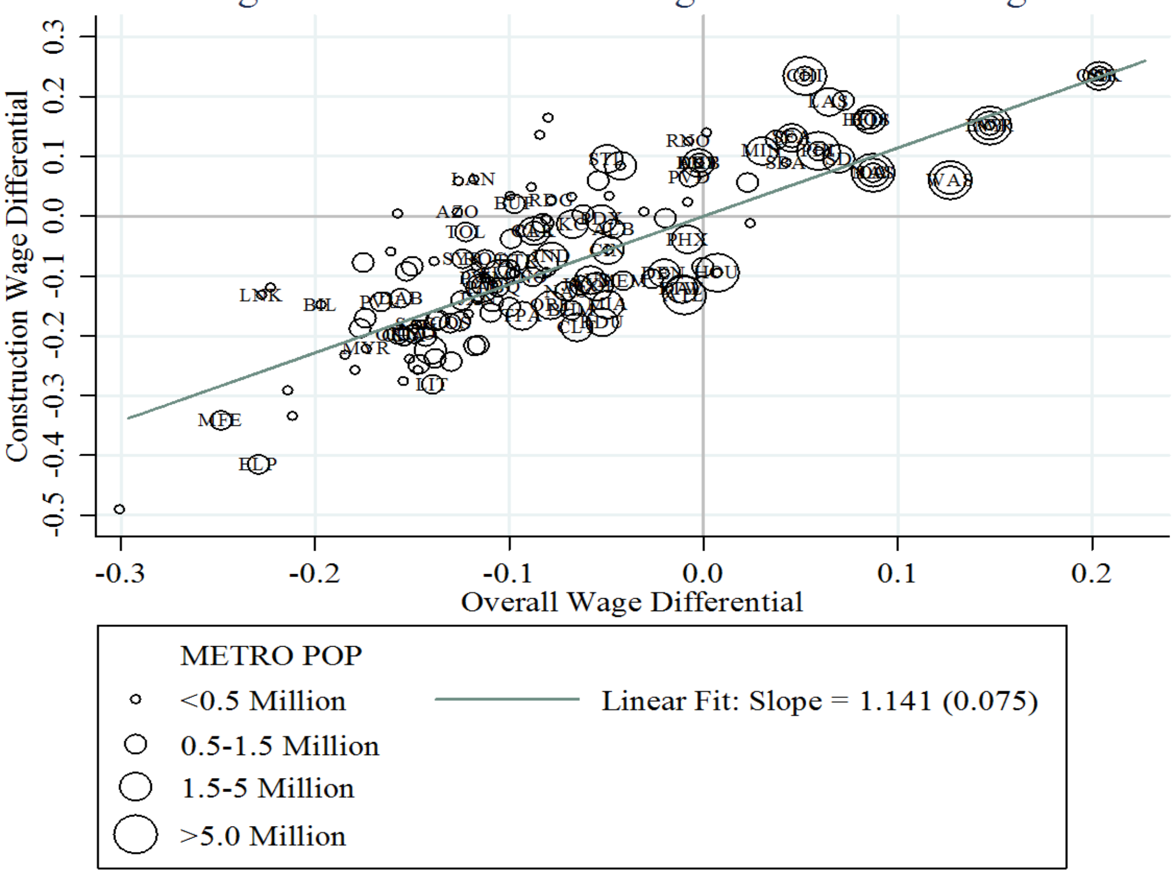

Figure C: Housing Prices vs. Housing Rents

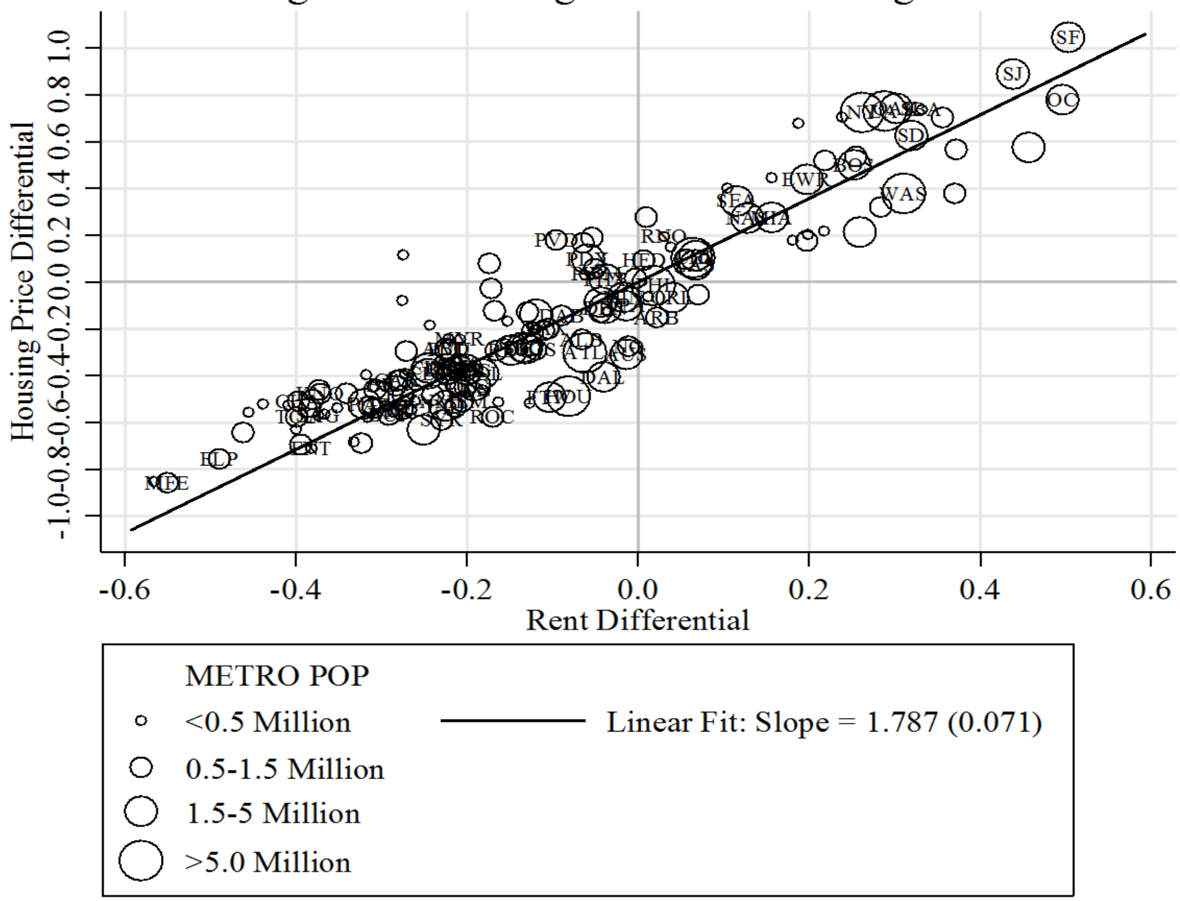

TABLE 1: MEASURES FOR SELECTED METROPOLITAN AREAS, RANKED BY LAND-VALUE DIFFERENTIAL

Name of Area	Population	Observed No. of Land Sales	*Adjusted Differentials* Land Value	Housing Cost	Wages (Const. Only)	*Raw Differentials* Regulation Index (z-score)	Geo Avail. Index (z-score)	Const. Cost Index	Land Value Rank
Metropolitan Areas:									
San Jose, CA PMSA	1,784,642	119	1.335	0.754	0.234	-0.041	1.604	0.173	1
New York, NY PMSA	9,747,281	388	1.263	0.497	0.151	0.658	0.493	0.302	2
Orange County, CA PMSA	3,026,786	133	1.123	0.705	0.072	0.179	1.066	0.092	3
San Francisco, CA PMSA	1,785,097	80	1.030	0.839	0.234	0.769	2.049	0.228	4
Seattle-Bellevue-Everett, WA PMSA	2,692,066	413	1.006	0.293	0.131	1.020	0.646	0.060	5
Washington, DC-MD-VA-WV PMSA	5,650,154	415	0.733	0.356	0.060	0.291	-0.766	0.003	11
Boston, MA-NH PMSA	3,552,421	357	0.321	0.437	0.161	2.216	0.183	0.174	25
Chicago, IL PMSA	8,710,824	1,344	0.209	0.095	0.234	-0.347	0.474	0.163	37
Phoenix-Mesa, AZ MSA	4,364,094	2,163	0.138	0.029	-0.039	0.633	-0.766	-0.105	38
Philadelphia, PA-NJ PMSA	5,332,822	360	0.046	0.018	0.109	1.320	-0.946	0.157	48
Atlanta, GA MSA	5,315,841	1,739	-0.108	-0.241	-0.133	-0.318	-1.235	-0.104	61
Riverside-San Bernardino, CA PMSA	4,143,113	1,117	-0.196	0.238	0.072	0.456	0.373	0.067	68
Houston, TX PMSA	5,219,317	537	-0.325	-0.378	-0.095	-0.972	-1.029	-0.125	82
Dallas, TX PMSA	4,399,895	438	-0.553	-0.297	-0.122	-0.734	-0.993	-0.145	104
Detroit, MI PMSA	4,373,040	340	-0.741	-0.230	0.088	-0.295	-0.263	0.047	126
Flint, MI PMSA	424,043	61	-1.535	-0.608	0.088	-0.863	-0.973	-0.014	161
Syracuse, NY MSA	725,610	45	-1.544	-0.522	-0.072	-1.288	-0.580	-0.021	162
Peoria-Pekin, IL MSA	357,144	25	-1.611	-0.511	0.164	-0.960	-1.192	0.040	163
Saginaw-Bay City-Midland, MI MSA	390,032	29	-1.825	-0.526	-0.182	-0.386	-0.649	-0.039	164
Rochester, NY MSA	1,093,434	81	-1.859	-0.493	-0.072	-0.458	0.019	0.002	165
Population Categories:									
Less than 500,000	18,655,922	2,712	-0.534	-0.214	-0.032	-0.271	-0.083	-0.053	4
500,000 to 1,500,000	54,211,795	7,366	-0.416	-0.193	-0.065	-0.190	-0.180	-0.059	3
1,500,000 to 5,000,000	91,110,643	13,999	0.078	0.041	0.007	0.067	0.091	-0.004	2
5,000,000+	49,824,250	5,525	0.492	0.201	0.079	0.180	-0.038	0.099	1
United States		29,671	0.684	0.374	0.142	1.001	0.996	0.141	
	total			*standard deviations (population weighted)*					

Land-value data from CoStar COMPS database for years 2006 to 2010. Wage and housing-cost data from 2006 to 2008 American Community Survey 3 percent sample. Wage differentials based on the average logarithm of hourly wages for full-time workers ages 25 to 55. Housing-cost differentials based on the average logarithm of rents and 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 2: MODEL OF HOUSING-COST DETERMINATION WITH CONSTANT NON-LAND INPUT PRICES

Specification	Basic Cobb-Douglas	CES	Rents Only	Housing Prices	Distance Adjusted
Dependent Variable	Hous. Cost	Hous. Cost	Hous. Rent	Hous. Price	Hous. Cost
	(1)	(2)	(3)	(4)	(5)
Land-Value Differential	0.363	0.374	0.248	0.454	0.354
	(0.028)	(0.031)	(0.029)	(0.027)	(0.032)
Land-Value Differential Squared		0.089	0.055	0.139	0.080
		(0.032)	(0.028)	(0.027)	(0.029)
Geographic Constraint Index: z-score	0.081	0.069	0.026	0.080	0.078
	(0.024)	(0.024)	(0.016)	(0.029)	(0.024)
Regulatory Index: z-score	0.075	0.082	0.038	0.094	0.068
	(0.014)	(0.014)	(0.012)	(0.017)	(0.013)
Constant	0.000	-0.042	-0.026	-0.065	-0.045
	(0.021)	(0.025)	(0.019)	(0.029)	(0.023)
Number of Observations	165	165	165	165	165
Adjusted R-squared	0.841	0.858	0.773	0.863	0.865
Elasticity of Substitution	1.00	0.242	0.409	-0.121	0.298
		(0.254)	(0.276)	(0.211)	(0.228)

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 1. Columns (1), (2), and (5) use both renter and owner observations, column (3) uses renters only, and column (4) uses owners only. Housing-cost and land-value differentials in column (5) distance-adjusted by driving time and distance to MSA center.

TABLE 3A: MODEL OF HOUSING-COST DETERMINATION WITH VARIABLE CONSTRUCTION COSTS

Specification	Basic Cobb-Douglas	Restricted Cobb-Douglas	Translog	Restricted Translog
Dependent Variable	Hous. Cost	Hous. Cost	Hous. Cost	Hous. Cost
	(1)	(2)	(3)	(4)
Land-Value Differential	0.312	0.312	0.332	0.329
	(0.032)	(0.033)	(0.035)	(0.044)
Construction-Cost Differential	0.677	0.688	0.610	0.671
	(0.131)	(0.033)	(0.112)	(0.044)
Land-Value Differential Squared			0.044	0.055
			(0.029)	(0.038)
Construction-Cost Differential Squared			-1.598	0.055
			(0.980)	(0.038)
Land-Value Differential X Construction-Cost Differential			0.204	-0.110
			(0.319)	(0.077)
Geographic Constraint Index: z-score	0.074	0.074	0.065	0.064
	(0.022)	(0.021)	(0.020)	(0.023)
Regulatory Index: z-score	0.048	0.047	0.054	0.046
	(0.013)	(0.011)	(0.013)	(0.012)
Constant	0.001	0.001	0.001	-0.019
	(0.020)	(0.020)	(0.031)	(0.020)
Number of Observations	159	159	159	159
Adjusted R-squared	0.881	0.884	0.888	0.899
p -value for constant-returns-to-scale restrictions		0.941		0.124
p -value for Cobb-Douglas restrictions	0.099	0.149		
p- value for all restrictions		0.143		
Elasticity of Substitution	1.000	1.000		0.500
				(0.315)

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 1. 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).

TABLE 3B: MODEL OF HOUSING-COST DETERMINATION WITH VARIABLE CONSTRUCTION WAGES

Specification	Basic Cobb-Douglas	Restricted Cobb-Douglas 1	Translog	Restricted Translog 1	Const. Cost Model	Restricted Cobb-Douglas 2
Dependent Variable	Hous. Cost (1)	Hous. Cost (2)	Hous. Cost (3)	Hous. Cost (4)	Const. Cost (5)	Hous. Cost (6)
Land-Value Differential	0.305	0.308	0.302	0.323	0.013	0.313
	(0.028)	(0.028)	(0.038)	(0.035)	(0.025)	(0.028)
Construction-Wage Differential	0.711	0.692	0.682	0.677	0.748	0.517
	(0.142)	(0.028)	(0.111)	(0.035)	(0.057)	(0.028)
Implied Capital-Cost Differential	-0.016	0.000	0.016	0.000	0.173	0.170
	(0.136)		(0.111)		(0.039)	
Land-Value Differential Squared			0.034	0.063		
			(0.034)	(0.034)		
Construction-Wage Differential Squared			-1.237	0.063		
			(0.786)	(0.034)		
Land-Value Differential X Construction-Wage Differential			0.410	-0.126		
			(0.157)	(0.068)		
Geographic Constraint Index: z-score	0.076	0.075	0.073	0.065	0.006	0.079
	(0.017)	(0.018)	(0.019)	(0.020)	(0.009)	(0.019)
Regulatory Index: z-score	0.056	0.053	0.059	0.055	0.020	0.060
	(0.014)	(0.013)	(0.013)	(0.012)	(0.010)	(0.013)
Constant	0.000	0.000	-0.012	-0.024	-0.001	0.000
	(0.019)	(0.019)	(0.027)	(0.022)	(0.011)	(0.019)
Number of Observations	165	165	165	165	159	165
Adjusted R-squared	0.891	0.826	0.904	0.837	0.755	0.832
p -value for constant-returns-to-scale restrictions		0.906		0.202		0.167
p -value for Cobb-Douglas restrictions	0.018	0.053				
p- value for all restrictions		0.024				
Elasticity of Substitution	1.000	1.000		0.411	1.000	
				(0.275)		

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 1. 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).

TABLE 4: MODEL OF HOUSING COSTS WITH DISAGGREGATED REGULATORY INDICES

Specification	Factor Loading		Restricted Translog w Cons Cost	Restricted Translog w Wage Cost
Dependent Variable		Reg Index	Hous. Cost	Hous. Cost
		(1)	(2)	(3)
Land-Value Differential			0.292	0.295
			(0.240)	(0.025)
Land-Value Differential Squared			0.056	0.071
			(0.019)	(0.021)
Geographic Constraint Index: z-score			0.048	0.055
			(0.016)	(0.014)
Approval Delay: z-score	0.29	0.509	0.033	0.024
		(0.036)	(0.040)	(0.032)
Local Political Pressure: z-score	0.22	0.186	0.017	0.019
		(0.061)	(0.023)	(0.024)
State Political Involvement: z-score	0.22	0.388	0.056	0.047
		(0.022)	(0.021)	(0.021)
Open Space: z-score	0.18	-0.027	-0.030	-0.035
		(0.033)	(0.012)	(0.014)
Exactions: z-score	0.15	-0.054	0.079	0.100
		(0.070)	(0.040)	(0.048)
Local Project Approval: z-score	0.15	0.212	-0.015	0.004
		(0.019)	(0.011)	(0.011)
Local Assembly: z-score	0.14	0.138	0.001	-0.009
		(0.046)	(0.018)	(0.019)
Density Restrictions: z-score	0.09	0.121	-0.076	-0.101
		(0.077)	(0.036)	(0.038)
Supply Restrictions: z-score	0.02	0.145	0.045	0.045
		(0.031)	(0.011)	(0.012)
State Court Involvement: z-score	-0.03	-0.140	0.057	0.041
		(0.020)	(0.012)	(0.012)
Local Zoning Approval: z-score	-0.04	-0.089	-0.008	0.016
		(0.069)	(0.039)	(0.036)
Constant		0.000	-0.020	-0.027
		(0.019)	(0.014)	(0.015)
Number of Observations		165	159	165
Adjusted R-squared		0.946	0.865	0.87
Elasticity of Substitution			0.462	0.319
			(0.169)	(0.190)

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 5: 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	1.656	2.011
	(0.128)	(0.167)
Construction-Cost Differential		-0.954
		(0.269)
Geographic Constraint Index: z-score	-0.012	-0.009
	(0.040)	(0.034)
Regulatory Index: z-score	-0.017	All
	(0.035)	Subindices
Constant	0.000	-0.002
	(0.034)	(0.028)
Number of Observations	165	159
Adjusted R-squared	0.781	0.803
Implied Land-Cost Share	0.604	0.497
	(0.047)	(0.041)
Implied Material-Cost Share		0.474
		(0.114)

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

	Productivity				
Name	Housing (Including Indices)	Unexplained Housing Component	Tradeables	Quality of Life	Total Amenity Value
Metropolitan Areas:					
San Jose, CA PMSA	-0.136	-0.004	0.202	0.124	0.224
New York, NY PMSA	0.042	0.081	0.153	0.076	0.183
Orange County, CA PMSA	-0.272	-0.134	0.100	0.160	0.167
San Francisco, CA PMSA	-0.352	-0.082	0.194	0.148	0.197
Seattle-Bellevue-Everett, WA PMSA	0.123	0.270	0.063	0.063	0.129
Washington, DC-MD-VA-WV PMSA	-0.093	-0.097	0.123	0.045	0.104
Boston, MA-NH PMSA	-0.254	0.018	0.079	0.086	0.082
Chicago, IL PMSA	0.104	0.052	0.048	0.004	0.057
Phoenix-Mesa, AZ MSA	-0.041	0.019	-0.003	0.012	0.001
Philadelphia, PA-NJ PMSA	0.045	0.029	0.050	-0.020	0.021
Atlanta, GA MSA	0.088	0.018	-0.011	-0.063	-0.052
Riverside-San Bernardino, CA PMSA	-0.268	-0.155	0.067	0.029	0.016
Houston, TX PMSA	0.192	0.021	-0.002	-0.109	-0.070
Dallas, TX PMSA	0.034	-0.102	-0.023	-0.079	-0.086
Detroit, MI PMSA	0.095	0.111	-0.021	-0.064	-0.056
Flint, MI PMSA	0.377	0.270	-0.040	-0.170	-0.116
Syracuse, NY MSA	0.142	-0.017	-0.141	-0.093	-0.153
Peoria-Pekin, IL MSA	0.348	0.190	-0.106	-0.109	-0.103
Saginaw-Bay City-Midland, MI MSA	0.023	-0.021	-0.168	-0.084	-0.187
Rochester, NY MSA	0.092	-0.073	-0.139	-0.090	-0.160
Population Categories:					
Less than 500,000	0.049	0.020	-0.070	-0.031	-0.065
500,000 to 1,500,000	0.029	-0.011	-0.060	-0.029	-0.061
1,500,000 to 5,000,000	-0.021	0.002	0.010	0.007	0.009
5,000,000+	0.002	0.007	0.075	0.024	0.072
United States	0.162	0.104	0.097	0.072	0.101
		standard deviations (population weighted)			

Land-value data from CoStar COMPS database for years 2006 to 2010. Wage and housing-cost data from 2006 to 2008 American Community Survey 3 percent sample. Wage differentials based on the average logarithm of hourly wages for full-time workers ages 25 to 55. Housing-cost differentials based on the average logarithm of rents and 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. Quality of life, federal tax, and inferred land values from Albouy (2009). Distance-adjusted land rent controls for driving time and distance to MSA center according to Google Maps.

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

	Dependent Variable			
	Tradeables Productivity (1)	Housing Productivity (2)	Homog Reg. Hous. Prod. (3)	Total Productivity (4)
Panel A: Population				
Log of Population	0.039	-0.063	-0.040	0.012
	(0.009)	(0.029)	(0.017)	(0.006)
Number of Observations	165	165	165	165
Adjusted R-squared	0.168	0.156	0.119	0.05
Panel B: Population Density				
Weighted Density Differential	0.088	-0.065	-0.020	0.042
	(0.012)	(0.037)	(0.019)	(0.004)
Number of Observations	165	165	165	165
Adjusted R-squared	0.529	0.1	0.013	0.442

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 1.. Tradeables productivity is 0.825 times the wage differential plus 0.025 times the land value differential. Housing productivity is inferred from column (5) of Table 4 taking into account the effect of geographic and regulatory variables. The measure in column (3) excludes the effect of regulatory variables. Total productivity is 0.64 tradeables productivity plus 0.212 times housing productivity.

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)
Panel A: Population				
Housing Productivity	-0.190	-0.182	-0.260	-0.217
	(0.037)	(0.028)	(0.037)	(0.030)
Natural Controls	X	X	X	X
Artificial Controls		X		X
Number of Observations	159	159	159	159
Adjusted R-squared	0.81	0.88	0.80	0.87

Robust standard errors, clustered by CMSA, in parentheses. Sample contains 159 observations. Housing Productivity predicted by regulation based upon the projection of housing costs on the subindices in column 3 of table 4. 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, 2006-2008

				Adjusted Differentials						*Raw Differentials*			*Productivity*		
Full Name	Population	Census Division	Obs. Land Sales	Land Value	Land Value (Dist. Adj.)	Housing Cost	Hous. Cost (Dist. Adj.)	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Avail. Index (z-score)	Const. Cost Index	Housing	Tradea-bles	Land Value Rank
<u>*Metropolitan Areas:*</u>															
San Jose, CA PMSA	1,784,642	9	119	1.335	1.121	0.754	0.736	0.204	0.234	-0.041	1.604	0.173	-0.136	0.202	1
New York, NY PMSA	9,747,281	2	388	1.263	1.351	0.497	0.509	0.147	0.151	0.658	0.493	0.302	0.042	0.153	2
Orange County, CA PMSA	3,026,786	9	133	1.123	0.977	0.705	0.698	0.087	0.072	0.179	1.066	0.092	-0.272	0.100	3
San Francisco, CA PMSA	1,785,097	9	80	1.030	0.930	0.839	0.826	0.204	0.234	0.769	2.049	0.228	-0.352	0.194	4
Seattle-Bellevue-Everett, WA PMSA	2,692,066	9	413	1.006	0.880	0.293	0.289	0.045	0.131	1.020	0.646	0.060	0.123	0.063	5
Bergen-Passaic, NJ PMSA	1,387,028	2	62	0.892	1.159	0.519	0.510	0.147	0.151	0.681	0.493	0.113	-0.137	0.144	6
Naples, FL MSA	318,537	5	55	0.879	0.715	0.347	0.362	0.024	-0.012	0.085	2.166		-0.068	0.042	7
Los Angeles-Long Beach, CA PMSA	9,848,011	9	742	0.841	0.898	0.557	0.552	0.087	0.072	0.373	1.066	0.092	-0.244	0.093	8
Miami, FL PMSA	2,500,625	5	398	0.812	0.726	0.252	0.249	-0.049	-0.148	1.113	2.215	-0.080	-0.079	-0.020	9
Oakland, CA PMSA	2,532,756	9	169	0.781	0.859	0.619	0.614	0.204	0.234	0.603	1.503	0.165	-0.230	0.188	10
Washington, DC-MD-VA-WV PMSA	5,650,154	5	415	0.733	0.915	0.356	0.373	0.127	0.060	0.291	-0.766	0.003	-0.093	0.123	11
Nassau-Suffolk, NY PMSA	2,875,904	2	180	0.701	1.157	0.544	0.586	0.147	0.151	0.737	0.493	0.302	-0.237	0.139	12
Middlesex-Somerset-Hunterdon, NJ PMSA	1,247,641	2	120	0.692	0.975	0.387	0.388	0.147	0.151	1.393	0.493	0.112	-0.083	0.139	13
Fort Lauderdale, FL PMSA	1,766,476	5	171	0.681	0.686	0.255	0.253	-0.049	-0.148	0.762	2.171	-0.105	-0.138	-0.024	14
Jersey City, NJ PMSA	597,924	2	69	0.677	0.318	0.362	0.366	0.147	0.151	0.084	0.178	0.113	-0.063	0.139	15
Santa Barbara-Santa Maria-Lompoc, CA MSA	407,057	9	28	0.676	0.684	0.563	0.583	0.043	0.089	1.000	2.661	0.069	-0.304	0.052	16
Ventura, CA PMSA	802,983	9	48	0.670	0.989	0.616	0.612	0.087	0.072	1.523	2.358	0.074	-0.369	0.089	16
West Palm BeachBoca Raton, FL MSA	1,279,950	5	191	0.629	0.772	0.215	0.214	0.000	-0.086	0.078	1.615	-0.131	-0.081	0.016	18
Las Vegas, NV-AZ MSA	2,141,893	8	893	0.579	0.423	0.089	0.074	0.065	0.190	-1.453	0.096	-0.115	0.199	0.068	19
San Luis Obispo-Atascadero-Paso Robles, CA MSA	266,971	9	27	0.524	0.539	0.520	0.513	0.002	0.140	1.380	1.701	0.033	-0.284	0.014	20
San Diego, CA MSA	3,053,793	9	395	0.493	0.411	0.532	0.530	0.070	0.095	0.262	1.586	0.060	-0.336	0.070	21
Tacoma, WA PMSA	796,836	9	119	0.419	0.559	0.026	0.029	0.045	0.131	1.852	0.316	0.037	0.169	0.048	22
Vallejo-Fairfield-Napa, CA PMSA	541,884	9	59	0.397	0.415	0.440	0.494	0.204	0.234	1.144	0.908	0.115	-0.184	0.178	23
Newark, NJ PMSA	2,045,344	2	146	0.347	0.549	0.380	0.376	0.147	0.151	0.695	0.022	0.126	-0.196	0.130	24
Boston, MA-NH PMSA	3,552,421	1	357	0.321	0.453	0.437	0.445	0.086	0.161	2.216	0.183	0.174	-0.254	0.079	25
Santa Rosa, CA PMSA	472,102	9	71	0.318	0.123	0.569	0.552	0.204	0.234	1.708	1.567	0.127	-0.337	0.176	26
Orlando, FL MSA	2,082,421	5	528	0.306	0.212	-0.021	-0.025	-0.079	-0.149	0.128	0.289	-0.097	-0.007	-0.057	27
Sarasota-Bradenton, FL MSA	688,126	5	189	0.273	0.201	0.119	0.114	-0.100	-0.152	1.077	1.739	-0.100	-0.160	-0.076	28
Monmouth-Ocean, NJ PMSA	1,217,783	2	113	0.272	0.777	0.329	0.338	0.147	0.151	2.115	0.493	0.302	-0.169	0.128	29
Portland-Vancouver, OR-WA PMSA	2,230,947	9	283	0.264	0.115	0.073	0.073	-0.053	-0.005	0.051	0.356	0.007	-0.022	-0.037	30
Provo-Orem, UT MSA	545,307	8	38	0.261	0.441	-0.263	-0.258	-0.166	-0.143	-0.041	1.404	-0.145	0.224	-0.131	30
Reading, PA MSA	407,125	2	27	0.258	0.155	-0.328	-0.324	-0.078	0.026	0.496	-0.645	0.010	0.398	-0.058	32
Trenton, NJ PMSA	366,222	2	45	0.243	0.795	0.237	0.213	0.147	0.151	2.382	-0.868	0.108	-0.085	0.128	33
Baltimore, MD PMSA	2,690,886	5	232	0.243	0.205	0.129	0.130	0.127	0.060	2.124	-0.389	-0.066	-0.040	0.111	34
Tampa-St. Petersburg-Clearwater, FL MSA	2,747,272	5	539	0.240	0.230	-0.059	-0.055	-0.093	-0.167	-0.712	0.551	-0.066	-0.003	-0.071	35
Olympia, WA PMSA	250,979	9	107	0.234	-0.043	0.001	-0.003	0.045	0.131	0.532	0.401	0.026	0.134	0.043	36
Chicago, IL PMSA	8,710,824	3	1,344	0.209	0.300	0.095	0.105	0.052	0.234	-0.347	0.474	0.163	0.104	0.048	37
Phoenix-Mesa, AZ MSA	4,364,094	8	2,163	0.138	0.246	0.029	0.022	-0.008	-0.039	0.633	-0.766	-0.105	-0.041	-0.003	38
Stockton-Lodi, CA MSA	674,860	9	96	0.130	-0.034	0.207	0.200	0.072	0.193	0.556	-0.856	0.073	-0.060	0.063	39
Reno, NV MSA	414,820	8	59	0.121	-0.130	0.163	0.148	-0.007	0.125	-0.848	1.235	-0.028	-0.066	-0.003	40
Newburgh, NY-PA PMSA	444,061	2	38	0.116	0.474	0.181	0.180	0.147	0.151	-0.441	-0.004	0.157	-0.068	0.125	41
Denver, CO PMSA	2,445,781	8	690	0.111	0.032	-0.077	-0.076	-0.020	-0.096	0.974	-0.634	-0.044	0.018	-0.014	42
Atlantic-Cape May, NJ PMSA	367,803	2	37	0.102	0.333	0.123	0.125	0.059	0.109	0.711	1.670	0.097	-0.043	0.051	43
Jacksonville, FL MSA	1,301,808	5	405	0.074	0.079	-0.165	-0.166	-0.063	-0.116	-0.403	0.821	-0.159	0.081	-0.050	44
Fort Myers-Cape Coral, FL MSA	586,908	5	258	0.070	-0.051	0.024	0.019	-0.062	0.002	-0.602	1.098	-0.124	-0.029	-0.050	45
Kenosha, WI PMSA	165,382	3	37	0.052	0.385	-0.171	-0.164	0.052	0.234	0.967	0.849	0.006	0.327	0.044	46

TABLE A1 (PROVISIONAL): LIST OF METROPOLITAN AREAS BY LAND PRICE DIFFERENTIAL, 2006-2008

				Adjusted Differentials						*Raw Differentials*			*Productivity*		
Full Name	Population	Cen-sus Div-ision	Obs. Land Sales	Land Value	Land Value (Dist. Adj.)	Housing Cost	Hous. Cost (Dist. Adj.)	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Avail. Index (z-score)	Const. Cost Index	Housing	Tradea-bles	Land Value Rank
Bridgeport, CT PMSA	470,094	1	94	0.047	0.042	0.414	0.379	0.147	0.151	0.381	0.493	0.101	-0.320	0.123	47
Philadelphia, PA-NJ PMSA	5,332,822	2	360	0.046	0.176	0.018	0.027	0.059	0.109	1.320	-0.946	0.157	0.045	0.050	48
Boulder-Longmont, CO PMSA	311,786	8	75	0.039	-0.076	0.111	0.114	-0.020	-0.096	3.706	0.623	-0.094	-0.193	-0.016	49
Salt Lake City-Ogden, UT MSA	1,567,650	8	91	0.034	0.052	-0.240	-0.240	-0.105	-0.096	-0.416	1.994	-0.130	0.156	-0.086	50
Melbourne-Titusville-Palm Bay, FL MSA	536,357	5	131	0.015	0.405	-0.105	-0.107	-0.114	-0.117	0.446	1.626	-0.079	0.001	-0.094	51
Wilmington-Newark, DE-MD PMSA	635,430	5	45	0.006	0.210	-0.015	-0.016	0.059	0.109	0.366	-0.731	0.053	0.067	0.049	52
Allentown-Bethlehem-Easton, PA MSA	706,374	2	52	-0.006	-0.299	-0.174	-0.170	-0.054	0.059	-0.337	-0.437	0.050	0.187	-0.045	53
Raleigh-Durham-Chapel Hill, NC MSA	1,589,388	5	551	-0.013	-0.064	-0.224	-0.221	-0.052	-0.177	0.417	-1.043	-0.236	0.070	-0.043	54
Albuquerque, NM MSA	841,428	8	97	-0.029	-0.097	-0.248	-0.255	-0.106	-0.118	0.217	-0.876	-0.104	0.129	-0.088	55
Savannah, GA MSA	343,092	5	61	-0.038	-0.153	-0.206	-0.212	-0.097	-0.096	-1.190	1.429	-0.183	0.099	-0.081	56
Colorado Springs, CO MSA	604,542	8	219	-0.039	-0.149	-0.234	-0.233	-0.130	-0.179	0.993	-0.370	-0.075	0.070	-0.109	57
Minneapolis-St. Paul, MN-WI MSA	3,269,814	4	383	-0.049	-0.086	-0.048	-0.049	0.030	0.109	-0.098	-0.515	0.124	0.085	0.024	58
Fort Pierce-Port St. Lucie, FL MSA	406,296	5	26	-0.064	-0.043	-0.030	-0.031	-0.081	-0.094	0.331	1.658		-0.082	-0.068	59
Norfolk-Virginia Beach-Newport News, VA-NC MSA	1,667,410	5	151	-0.090	-0.035	-0.049	-0.046	-0.083	-0.080	-0.180	1.413	-0.122	-0.061	-0.071	60
Atlanta, GA MSA	5,315,841	5	1,739	-0.108	-0.042	-0.241	-0.232	-0.010	-0.133	-0.318	-1.235	-0.104	0.088	-0.011	61
Tucson, AZ MSA	1,020,200	8	527	-0.116	-0.145	-0.109	-0.095	-0.118	-0.217	2.011	-0.332	-0.139	-0.105	-0.100	62
Fort Collins-Loveland, CO MSA	298,382	8	124	-0.130	-0.257	-0.144	-0.167	-0.117	-0.084	0.924	0.057	-0.090	0.019	-0.100	63
Lakeland-Winter Haven, FL MSA	583,403	5	212	-0.154	-0.145	-0.233	-0.239	-0.136	-0.173	-0.091	0.101	-0.075	0.038	-0.116	64
Modesto, CA MSA	510,385	9	60	-0.164	-0.084	0.121	0.111	0.038	0.127	0.019	-0.750	0.074	-0.101	0.027	65
Visalia-Tulare-Porterville, CA MSA	429,668	9	25	-0.186	-0.232	-0.136	-0.142	-0.031	0.007	0.350	-0.505		0.061	-0.030	66
Merced, CA MSA	245,321	9	49	-0.190	-0.064	-0.032	-0.024	-0.008	0.023	0.632	-0.946		-0.032	-0.011	67
Riverside-San Bernardino, CA PMSA	4,143,113	9	1,117	-0.196	-0.048	0.238	0.241	0.087	0.072	0.456	0.373	0.067	-0.268	0.067	68
Nashville, TN MSA	1,495,419	6	370	-0.199	-0.360	-0.291	-0.299	-0.071	-0.126	-1.005	-0.819	-0.123	0.116	-0.063	68
Madison, WI MSA	491,357	3	124	-0.206	0.366	-0.100	-0.108	-0.089	0.049	0.266	-0.890	-0.007	0.051	-0.078	70
Asheville, NC MSA	251,894	5	30	-0.222	-0.589	-0.169	-0.201	-0.212	-0.334	-1.326	1.780	-0.269	-0.158	-0.180	71
Charlotte-Gastonia-Rock Hill, NC-SC MSA	1,937,309	5	732	-0.237	-0.347	-0.311	-0.302	-0.065	-0.186	-0.854	-1.206	-0.237	0.083	-0.060	72
Greeley, CO PMSA	254,759	8	121	-0.251	-0.289	-0.289	-0.278	-0.020	-0.096	-0.465	-0.949	-0.158	0.122	-0.023	73
Fresno, CA MSA	1,063,899	9	185	-0.252	-0.493	0.001	-0.007	-0.020	-0.004	1.055	-0.817	0.076	-0.101	-0.023	74
Richmond-Petersburg, VA MSA	1,119,459	5	165	-0.271	-0.291	-0.169	-0.173	-0.026	-0.105	-0.961	-1.010	-0.128	-0.011	-0.029	75
Providence-Fall River-Warwick, RI-MA MSA	1,201,855	1	35	-0.283	-0.391	0.109	0.106	-0.007	0.065	2.667	0.493	0.071	-0.165	-0.013	76
Boise City, ID MSA	571,271	8	81	-0.283	-0.391	-0.266	-0.284	-0.143	-0.202	-1.094	0.299	-0.116	0.013	-0.125	77
Austin-San Marcos, TX MSA	1,705,075	7	187	-0.293	-0.414	-0.222	-0.223	-0.058	-0.107	-0.813	-1.250	-0.213	0.035	-0.055	78
Lancaster, PA MSA	507,766	2	49	-0.304	-0.417	-0.251	-0.254	-0.099	-0.039	0.085	-0.863	-0.066	0.112	-0.089	79
Daytona Beach, FL MSA	587,512	5	77	-0.307	-0.370	-0.118	-0.120	-0.156	-0.137	0.382	-1.379	-0.112	-0.094	-0.136	80
New Orleans, LA MSA	1,211,035	7	33	-0.323	-0.544	-0.205	-0.220	-0.088	-0.102	-2.311	2.132	-0.115	0.014	-0.081	81
Houston, TX PMSA	5,219,317	7	537	-0.325	-0.355	-0.378	-0.377	0.007	-0.095	-0.972	-1.029	-0.125	0.192	-0.002	82
Charleston-North Charleston, SC MSA	659,191	5	155	-0.337	-0.421	-0.095	-0.104	-0.109	-0.162	-1.632	1.445	-0.193	-0.144	-0.099	83
Indianapolis, IN MSA	1,823,690	3	165	-0.344	-0.445	-0.442	-0.434	-0.078	-0.068	-1.441	-1.360	-0.064	0.271	-0.073	84
York, PA MSA	428,937	2	31	-0.349	-0.576	-0.313	-0.315	-0.068	0.032	0.997	-0.853	-0.026	0.215	-0.065	85
Milwaukee-Waukesha, WI PMSA	1,559,667	3	185	-0.357	-0.438	-0.117	-0.114	-0.043	0.084	0.348	0.558	0.046	0.057	-0.044	86
Fayetteville-Springdale-Rogers, AR MSA	425,685	7	48	-0.364	-0.530	-0.350	-0.350	-0.151	-0.238	-1.002	-0.053	-0.277	0.048	-0.134	87
Champaign-Urbana, IL MSA	195,671	3	20	-0.371	-0.818	-0.387	-0.427	-0.157	0.004	-0.982	-1.360	0.041	0.263	-0.139	88
Lexington, KY MSA	554,107	6	20	-0.401	-0.314	-0.365	-0.390	-0.138	-0.175	-0.075	-1.148	-0.124	0.099	-0.124	89
Cincinnati, OH-KY-IN PMSA	1,776,911	3	234	-0.402	-0.465	-0.318	-0.319	-0.049	-0.057	-1.319	-0.939	-0.078	0.140	-0.051	90
Billings, MT MSA	144,797	8	20	-0.407	-0.642	-0.414	-0.415	-0.197	-0.148	-0.672	-0.889	-0.099	0.167	-0.173	91
Columbus, OH MSA	1,718,303	3	268	-0.408	-0.541	-0.318	-0.318	-0.055	-0.118	0.039	-1.310	-0.050	0.093	-0.055	92
Harrisburg-Lebanon-Carlisle, PA MSA	667,425	2	56	-0.410	-0.501	-0.344	-0.342	-0.083	-0.012	0.430	-0.287	-0.016	0.198	-0.078	92
St. Louis, MO-IL MSA	2,733,694	4	296	-0.480	-0.371	-0.317	-0.306	-0.050	0.096	-1.400	-0.902	0.039	0.239	-0.053	94

TABLE A1 (PROVISIONAL): LIST OF METROPOLITAN AREAS BY LAND PRICE DIFFERENTIAL, 2006-2008

				Adjusted Differentials						*Raw Differentials*			*Productivity*		
Full Name	Population	Census Division	Obs. Land Sales	Land Value	Land Value (Dist. Adj.)	Housing Cost	Hous. Cost (Dist. Adj.)	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Avail. Index (z-score)	Const. Cost Index	Housing	Tradeables	Land Value Rank
McAllen-Edinburg-Mission, TX MSA	741,152	7	91	-0.501	-0.552	-0.804	-0.809	-0.248	-0.342	-1.072	-1.384	-0.266	0.390	-0.217	95
Louisville, KY-IN MSA	1,099,588	6	88	-0.506	-0.756	-0.417	-0.426	-0.119	-0.105	-1.098	-0.825	-0.084	0.178	-0.111	96
Rockford, IL MSA	409,058	3	63	-0.515	-0.218	-0.482	-0.481	-0.084	0.136	-1.199	-1.325	0.098	0.428	-0.082	97
Gary, IN PMSA	657,809	3	90	-0.518	-0.364	-0.368	-0.368	0.052	0.234	-1.457	0.070	0.030	0.393	0.030	98
Cleveland-Lorain-Elyria, OH PMSA	2,192,053	3	139	-0.522	-0.544	-0.345	-0.340	-0.087	-0.025	-0.614	0.497	0.005	0.163	-0.085	99
Green Bay, WI MSA	247,319	3	38	-0.528	-0.701	-0.345	-0.348	-0.099	-0.081	0.531	-0.322	-0.034	0.118	-0.095	100
Greensboro-Winston-Salem-High Point, NC MSA	1,416,374	5	316	-0.536	-0.564	-0.421	-0.424	-0.130	-0.243	-0.954	-1.280	-0.245	0.070	-0.121	101
Dutchess County, NY PMSA	293,562	2	25	-0.540	-0.739	0.223	0.192	0.147	0.151	0.189	0.493	0.157	-0.269	0.108	102
Lincoln, NE MSA	281,531	4	20	-0.542	-0.578	-0.479	-0.482	-0.228	-0.132	0.825	-1.353	-0.121	0.211	-0.201	103
Dallas, TX PMSA	4,399,895	7	438	-0.553	-0.540	-0.297	-0.296	-0.011	-0.122	-0.734	-0.993	-0.145	0.034	-0.023	104
Worcester, MA-CT PMSA	547,274	1	40	-0.557	-0.517	0.115	0.112	0.086	0.161	3.115	0.183	0.106	-0.156	0.057	105
Tulsa, OK MSA	873,304	7	205	-0.563	-0.723	-0.459	-0.472	-0.146	-0.248	-1.537	-1.130	-0.223	0.098	-0.135	106
Brazoria, TX PMSA	309,208	7	45	-0.571	-0.551	-0.453	-0.431	0.007	-0.095	-1.181	-1.029	-0.125	0.206	-0.008	106
Bakersfield, CA MSA	807,407	9	50	-0.580	-0.806	-0.056	-0.057	0.023	0.056	0.252	-0.278	0.060	-0.074	0.004	108
Myrtle Beach, SC MSA	263,868	5	50	-0.598	-0.663	-0.228	-0.226	-0.174	-0.222	-1.671	1.512		-0.122	-0.158	109
Memphis, TN-AR-MS MSA	1,230,253	6	144	-0.611	-0.661	-0.396	-0.404	-0.041	-0.108	1.483	-0.850	-0.142	0.130	-0.049	110
Fort Worth-Arlington, TX PMSA	2,113,278	7	345	-0.611	-0.487	-0.385	-0.398	-0.011	-0.122	-0.771	-1.195	-0.176	0.108	-0.024	111
Dayton-Springfield, OH MSA	933,312	3	62	-0.611	-0.760	-0.456	-0.470	-0.126	-0.176	-1.089	1.449	-0.096	0.137	-0.119	112
Hamilton-Middletown, OH PMSA	363,184	3	21	-0.617	-0.484	-0.380	-0.386	-0.049	-0.057	-0.331	-1.097	-0.094	0.153	-0.056	113
Birmingham, AL MSA	997,770	6	78	-0.627	-0.909	-0.307	-0.307	-0.068	-0.158	-0.737	-0.746	-0.117	0.000	-0.072	114
Hartford, CT MSA	1,231,125	1	134	-0.631	-0.587	0.092	0.078	0.083	0.160	0.378	-0.322	0.098	-0.148	0.053	115
Gainesville, FL MSA	243,574	5	25	-0.645	-0.977	-0.154	-0.166	-0.155	-0.276	-0.256	-0.696	-0.134	-0.249	-0.144	116
Hickory-Morganton-Lenoir, NC MSA	365,364	5	67	-0.660	-0.784	-0.503	-0.516	-0.214	-0.291	-1.272	-0.432	-0.308	0.085	-0.193	117
San Antonio, TX MSA	1,928,154	7	113	-0.665	-0.794	-0.519	-0.534	-0.141	-0.224	-0.702	-1.278	-0.192	0.151	-0.133	118
Richland-Kennewick-Pasco, WA MSA	245,649	9	20	-0.678	-1.137	-0.421	-0.430	-0.049	0.034	0.869	-0.846	-0.042	0.253	-0.057	119
Chattanooga, TN-GA MSA	510,388	6	43	-0.679	-1.000	-0.452	-0.447	-0.154	-0.201	-1.498	-0.201	-0.152	0.099	-0.144	120
Baton Rouge, LA MSA	685,419	7	54	-0.694	-0.918	-0.315	-0.322	-0.095	-0.075	-1.643	0.165	-0.153	0.057	-0.096	121
Kansas City, MO-KS MSA	2,005,888	4	239	-0.726	-0.825	-0.370	-0.375	-0.067	-0.013	-1.611	-1.152	0.044	0.155	-0.074	122
El Paso, TX MSA	751,296	7	55	-0.729	-0.851	-0.676	-0.684	-0.229	-0.415	0.773	-1.185	-0.239	0.148	-0.207	123
Omaha, NE-IA MSA	799,130	4	83	-0.733	-0.965	-0.451	-0.453	-0.124	-0.141	-1.244	-1.270	-0.097	0.133	-0.121	124
Pittsburgh, PA MSA	2,287,106	2	136	-0.735	-0.796	-0.459	-0.451	-0.114	-0.120	-0.214	-0.001	0.011	0.156	-0.112	125
Detroit, MI PMSA	4,373,040	3	340	-0.741	-0.689	-0.230	-0.232	-0.002	0.088	-0.295	-0.263	0.047	0.095	-0.021	126
Racine, WI PMSA	200,601	3	24	-0.767	-0.678	-0.228	-0.224	-0.043	0.084	-0.701	1.144	0.010	0.085	-0.054	127
Knoxville, TN MSA	785,490	6	145	-0.871	-0.877	-0.418	-0.424	-0.149	-0.197	-0.952	0.403	-0.206	0.027	-0.145	128
Greenville-Spartanburg-Anderson, SC MSA	159,057	5	280	-0.888	-0.958	-0.474	-0.484	-0.121	-0.163	-1.835	-0.817	-0.257	0.106	-0.122	129
Ann Arbor, MI PMSA	630,518	3	76	-0.892	-0.853	-0.101	-0.122	-0.002	0.088	0.193	-0.967	0.014	-0.059	-0.024	130
Springfield, MO MSA	383,637	4	34	-0.895	-0.992	-0.551	-0.556	-0.223	-0.120	-1.546	-1.114	-0.103	0.218	-0.206	131
Fort Wayne, IN MSA	528,408	3	32	-0.906	-1.234	-0.626	-0.631	-0.150	-0.084	-2.281	-1.307	-0.109	0.320	-0.146	132
Oklahoma City, OK MSA	1,213,704	7	253	-0.917	-1.073	-0.441	-0.446	-0.157	-0.198	-0.903	-1.312	-0.180	0.040	-0.153	133
Des Moines, IA MSA	536,664	4	64	-0.933	-1.198	-0.390	-0.406	-0.100	-0.089	-1.686	-1.135	-0.116	0.075	-0.106	134
Wichita, KS MSA	589,195	4	44	-0.940	-1.082	-0.603	-0.608	-0.153	-0.093	-2.230	-1.350	-0.181	0.284	-0.150	135
Akron, OH PMSA	699,935	3	79	-0.968	-1.199	-0.370	-0.376	-0.087	-0.025	-0.262	-1.122	-0.029	0.103	-0.096	136
Little Rock-North Little Rock, AR MSA	657,416	7	90	-0.970	-1.240	-0.412	-0.426	-0.140	-0.281	-1.699	-0.777	-0.161	-0.067	-0.139	137
Bryan-College Station, TX MSA	179,992	7	26	-1.020	-1.189	-0.394	-0.420	-0.185	-0.232	0.234	-1.123	-0.201	-0.053	-0.178	138
Cedar Rapids, IA MSA	209,226	4	25	-1.042	-1.417	-0.482	-0.489	-0.139	-0.075	-1.014	-1.260	-0.093	0.160	-0.140	139
Jackson, MS MSA	483,852	6	37	-1.060	-1.109	-0.426	-0.439	-0.116	-0.140	-1.512	-0.890	-0.157	0.047	-0.123	140
Portland, ME MSA	256,178	1	20	-1.061	-1.163	0.026	0.011	-0.112	-0.104	1.682	0.923	-0.088	-0.376	-0.119	141
Augusta-Aiken, GA-SC MSA	516,357	5	59	-1.076	-1.164	-0.488	-0.486	-0.116	-0.216	-2.080	-0.933	-0.171	0.044	-0.123	142

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				Adjusted Differentials						*Raw Differentials*			*Productivity*		
Full Name	Population	Census Division	Obs. Land Sales	Land Value	Land Value (Dist. Adj.)	Housing Cost	Hous. Cost (Dist. Adj.)	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Avail. Index (z-score)	Const. Cost Index	Housing	Tradeables	Land Value Rank
Scranton-Wilkes Barre-Hazleton, PA MSA	614,565	2	26	-1.076	-1.013	-0.470	-0.467	-0.177	-0.188	-0.356	-0.060	0.013	0.049	-0.173	143
Columbia, SC MSA	627,630	5	64	-1.093	-1.353	-0.377	-0.384	-0.138	-0.238	-1.567	-0.705	-0.240	-0.089	-0.141	144
Mobile, AL MSA	591,599	6	104	-1.100	-1.000	-0.412	-0.402	-0.174	-0.170	-1.934	-0.035	-0.159	0.001	-0.171	145
Brownsville-Harlingen-San Benito, TX MSA	396,371	7	33	-1.101	-1.552	-0.794	-0.799	-0.301	-0.490	-1.867	-0.115		0.123	-0.276	146
Biloxi-Gulfport-Pascagoula, MS MSA	355,075	6	26	-1.121	-1.237	-0.396	-0.406	-0.145	-0.181	-1.923	1.047	-0.182	-0.027	-0.148	147
Canton-Massillon, OH MSA	408,005	3	29	-1.142	-0.713	-0.523	-0.518	-0.161	-0.059	-1.634	-0.831	-0.071	0.200	-0.161	148
Kalamazoo-Battle Creek, MI MSA	462,250	3	23	-1.173	-1.387	-0.483	-0.479	-0.127	0.006	-0.238	-0.960	-0.066	0.212	-0.134	149
Pensacola, FL MSA	455,102	5	86	-1.181	-1.412	-0.341	-0.365	-0.179	-0.257	-1.712	1.071	-0.142	-0.156	-0.178	150
Lansing-East Lansing, MI MSA	453,603	3	41	-1.209	-1.501	-0.392	-0.405	-0.118	0.062	-0.066	-1.103	-0.016	0.165	-0.128	151
Buffalo-Niagara Falls, NY MSA	1,123,804	2	83	-1.210	-1.418	-0.500	-0.504	-0.097	0.021	-0.686	-0.523	0.029	0.238	-0.111	152
Danville city Davenport-Moline-Rock Island, IA-IL MSA	362,790	4	22	-1.239	-0.652	-0.505	-0.537	-0.126	0.059	-1.799	-1.211	-0.055	0.272	-0.135	153
Grand Rapids-Muskegon-Holland, MI MSA	1,157,672	3	94	-1.279	-1.345	-0.435	-0.440	-0.109	-0.144	-0.586	-0.988	-0.127	0.021	-0.122	154
Beaumont-Port Arthur, TX MSA	378,477	7	74	-1.295	-1.704	-0.601	-0.610	-0.081	-0.006	-1.368	-0.532	-0.181	0.304	-0.099	155
Appleton-Oshkosh-Neenah, WI MSA	385,264	3	40	-1.311	-1.537	-0.414	-0.409	-0.100	0.034	-0.641	-0.576	-0.073	0.152	-0.115	156
Toledo, OH MSA	631,275	3	55	-1.311	-1.477	-0.513	-0.520	-0.122	-0.026	-1.257	-0.527	-0.014	0.197	-0.134	157
Montgomery, AL MSA	354,108	6	24	-1.343	-1.545	-0.444	-0.464	-0.147	-0.257	-1.923	-0.917	-0.208	-0.077	-0.155	157
Youngstown-Warren, OH MSA	554,614	3	21	-1.398	-1.530	-0.603	-0.615	-0.175	-0.078	-0.968	-0.929	-0.044	0.231	-0.179	159
Albany-Schenectady-Troy, NY MSA	906,208	2	82	-1.475	-1.594	-0.201	-0.204	-0.046	-0.021	-0.492	-0.320	-0.008	-0.126	-0.075	160
Flint, MI PMSA	424,043	3	61	-1.535	-1.696	-0.608	-0.632	-0.002	0.088	-0.863	-0.973	-0.014	0.377	-0.040	161
Syracuse, NY MSA	725,610	2	45	-1.544	-1.528	-0.522	-0.526	-0.124	-0.072	-1.288	-0.580	-0.021	0.142	-0.141	162
Peoria-Pekin, IL MSA	357,144	3	25	-1.611	-1.776	-0.511	-0.523	-0.080	0.164	-0.960	-1.192	0.040	0.348	-0.106	163
Saginaw-Bay City-Midland, MI MSA	390,032	3	29	-1.825	-1.829	-0.526	-0.523	-0.148	-0.182	-0.386	-0.649	-0.039	0.023	-0.168	164
Rochester, NY MSA	1,093,434	2	81	-1.859	-1.887	-0.493	-0.501	-0.112	-0.072	-0.458	0.019	0.002	0.092	-0.139	165
<u>*Census Divisions:*</u>															
New England	7,258,947	1	680	-0.073	-0.020	0.284	0.282	0.067	0.135	1.909	0.195	0.125	-0.223	0.053	5
Middle Atlantic	35,391,729	2	2,251	0.267	0.376	0.159	0.167	0.067	0.091	0.584	0.022	0.166	0.006	0.062	2
East North Central	32,900,944	3	3,759	-0.479	-0.484	-0.229	-0.229	-0.034	0.060	-0.538	-0.246	0.029	0.138	-0.040	6
West North Central	11,171,569	4	1,210	-0.513	-0.544	-0.297	-0.298	-0.057	0.027	-1.058	-0.930	0.021	0.164	-0.060	7
South Atlantic	41,293,071	5	8,403	0.131	0.137	-0.026	-0.023	-0.028	-0.104	-0.018	0.057	-0.109	-0.019	-0.020	3
East South Central	8,457,649	6	1,079	-0.653	-0.778	-0.378	-0.385	-0.105	-0.150	-0.758	-0.561	-0.140	0.076	-0.103	9
West South Central	23,188,778	7	2,627	-0.547	-0.624	-0.395	-0.399	-0.068	-0.158	-0.965	-0.861	-0.167	0.108	-0.070	8
Mountain	15,526,710	8	5,198	0.121	0.097	-0.070	-0.074	-0.042	-0.053	0.285	-0.101	-0.100	0.044	-0.031	4
Pacific	38,613,212	9	4,395	0.584	0.559	0.440	0.436	0.086	0.105	0.514	0.914	0.090	-0.189	0.086	1
<u>*Population Categories:*</u>															
Less than 500,000	18,655,922		2,712	-0.534	-0.591	-0.214	-0.222	-0.068	-0.032	-0.271	-0.083	-0.053	0.049	-0.070	4
500,000 to 1,500,000	54,211,795		7,366	-0.416	-0.467	-0.193	-0.197	-0.060	-0.065	-0.190	-0.180	-0.059	0.029	-0.060	3
1,500,000 to 5,000,000	91,110,643		13,999	0.078	0.072	0.041	0.041	0.010	0.007	0.067	0.091	-0.004	-0.021	0.010	2
5,000,000+	49,824,250		5,525	0.492	0.575	0.201	0.208	0.076	0.079	0.180	-0.038	0.099	0.002	0.075	1

TABLE A2: SUMMARY STATISTICS FOR OBSERVED LAND SALES

Observations	31,327
Mean Lot Size (Acres)	31.694
	(301.459)
Mean Price Per Acre (Dollars)	931,458
	(4,638,456)
No Proposed Use	19.8%
Proposed Use Commercial	0.6%
Proposed Use Industrial	9.6%
Proposed Use Retail	9.9%
Proposed Use Single Family	8.6%
Proposed Use MultiFamily	4.7%
Proposed Use Office	7.5%
Proposed Use Apartment	3.4%
Proposed Use Hold for Development	6.9%
Proposed Use Hold for Investment	2.3%
Proposed Use Mixed Use	2.2%
Proposed Use Medical	1.5%
Proposed Use Apartment	1.0%
Has Valid Address	22,405
Mean Meters from MSA Center	37,136
	(41,391)
Mean Seconds from MSA Center	1,868
	(1,635)
Sale in 2005	0.3%
Sale in 2006	0.6%
Sale in 2007	12.6%
Sale in 2008	40.7%
Sale in 2009	33.6%
Sale in 2010	12.3%

Data from CoStar COMPS database. Downloaded from June 28 to June 30, and on September 7, 2010.

TABLE A3: LAND VALUE AUXILLIARY REGRESSION

	Dependent Variable: Log Price per Acre			
	(1)	(2)	(3)	(4)
Log lot size (acres)	-0.637	-0.594	-0.591	-0.593
	(0.010)	(0.010)	(0.010)	(0.010)
Log driving distance to city center (meters)		-0.234		0.235
		(0.033)		(0.098)
Log driving time to city center (seconds)			-0.357	-0.672
			(0.041)	(0.122)
No planned use	-0.192	-0.198	-0.192	-0.186
	(0.032)	(0.041)	(0.040)	(0.039)
Planned use: commercial	-0.382	-0.325	-0.320	-0.317
	(0.083)	(0.102)	(0.101)	(0.101)
Planned use: Industrial	-0.326	-0.358	-0.361	-0.362
	(0.026)	(0.027)	(0.027)	(0.026)
Planned use: retail	0.276	0.275	0.272	0.268
	(0.025)	(0.031)	(0.031)	(0.030)
Planned use: single family	-0.137	-0.116	-0.102	-0.092
	(0.025)	(0.032)	(0.033)	(0.032)
Planned use: multi-family	-0.132	-0.157	-0.152	-0.142
	(0.035)	(0.042)	(0.042)	(0.041)
Planned use: office	-0.011	-0.022	-0.025	-0.026
	(0.031)	(0.033)	(0.032)	(0.032)
Planned use: apartment	0.304	0.169	0.165	0.172
	(0.061)	(0.058)	(0.058)	(0.058)
Planned use: hold for development	0.012	-0.001	0.003	0.008
	(0.039)	(0.040)	(0.039)	(0.039)
Planned use: hold for investment	-0.362	-0.355	-0.346	-0.339
	(0.055)	(0.068)	(0.067)	(0.065)
Planned use: mixed use	0.280	0.378	0.381	0.390
	(0.074)	(0.048)	(0.049)	(0.051)
Planned use: medical	0.179	0.200	0.192	0.182
	(0.045)	(0.057)	(0.056)	(0.057)
Planned use: parking	0.247	0.101	0.100	0.113
	(0.078)	(0.084)	(0.084)	(0.085)
Number of Observations	31,252	22,349	22,349	22,349
Adjusted R-squared	0.609	0.616	0.618	0.619

Robust standard errors, clustered by MSA/PMSA, reported in parentheses. Land-value data from CoStar COMPS database for years 2006 to 2010. Driving distance and driving time to city center from Google Maps automated programming interface. All specifications include a full set of dummies for MSA/PMSA and quarter of sale (not shown)