

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, slightly over 20 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 one. 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 constitutes the largest share of household expenditure among all goods, and its value depends fundamentally on the land upon which it is built. Land values are extremely heterogeneous, 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. 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. Using recent measures by Gyourko, Saiz, and Summers (2008) and Saiz (2010), we are able to investigate how local housing productivity is influenced by artificial and natural constraints to development due to regulation and geography.

We find that, on average, 20 percent of housing costs are due to land: this share ranges from 0.15 to 0.27 in low to high-value areas, implying an elasticity of substitution between land and other inputs in production on average of about 0.94. Consistent estimation of these parameters requires controlling for regulatory and geographic constraints: a standard deviation increase in either of our basic constraint measures increases the cost of producing housing between 5 and 8 percent. We also examine the role of disaggregated measures of regulation and find that exactions, supply restrictions, and state and local court involvement predict the lowest productivity levels. Overall,

housing productivity differences across metros are large, with a standard deviation of 19 percent of total costs, with a quarter 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, enough to compensate local residents for higher housing costs.

The most prominent 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 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 entail the use of any additional 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 an input. This approach is taken in Epple, Gordon, and Seig (2010), who use separately assessed land and structure values for houses in Alleghany County, PA, and find land's

¹Older 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).

cost share to be 14 percent. While our cost-share estimate for Pittsburgh is similar at 18.6 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 array of regulations.² The variation across, rather than within, cities produces a point estimate for the elasticity of substitution near one, consistent with the newer literature that estimates this parameter, such as Epple, Gordon, and Seig (2010), and Thorsnes (1997), and in contrast with much of the older literature that uses within-city variation: see McDonald (1981) for a survey of this literature.

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 .

²Although 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

$$Y_j = F^Y(L, M; A_j^Y) \quad (1)$$

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 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 competitive³, then in equilibrium housing price equals the unit cost:

$$c^Y(r_j, v_j; A_j^Y) = p_j \quad (2)$$

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

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

where \hat{z}^j represents, for any attribute z , city j 's log deviation from the national average, \bar{z} , i.e. $\hat{z}^j = \ln z^j - \ln \bar{z} \cong (z^j - \bar{z})/\bar{z}$, ϕ^L is the average cost share of land in housing, and \hat{A}_j^Y 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 it corresponds to the proportional reduction in costs. Rearranged, this equation measures unobserved local home-productivity from

³Although 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.

how high land and material costs are relative to housing costs:

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

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

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

where σ^Y is the elasticity of substitution between land and non-land inputs.⁴ 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 $\sigma^Y < 1$.

2.2 Empirical Model

The second-order approximation of the cost function we employ is equivalent to the translog cost function of Christensen et al. (1973) (see, e.g., Fuss and McFadden 1978):

$$\hat{p}_j = \beta_1 \hat{r}_j + \beta_2 \hat{v}_j + \beta_3 (\hat{r}_j)^2 + \beta_4 (\hat{v}_j)^2 + \beta_5 (\hat{r}_j \hat{v}_j) + \gamma Z^j + \varepsilon_j \quad (6)$$

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

$$\hat{A}_Y^j = Z^j(-\gamma) + \hat{A}_Y^{0j} \quad (7)$$

⁴A model using factor-specific productivity differences is presented in Appendix A.

and $\hat{A}_Y^{0j} = -\varepsilon_j$ is the residual component of housing productivity.⁵ CRS imply the three restrictions

$$\beta_1 = 1 - \beta_2 \quad (8a)$$

$$\beta_3 = \beta_4 = -\beta_5/2 \quad (8b)$$

in which case $\phi^L = \beta_1$ and, with factor-neutral productivity, $\sigma^Y = 1 - 2\beta_3/[\beta_1(1 - \beta_1)]$. The functional form of the cost function resulting from the second-order approximation we employ (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 (6) amounts to the three restrictions:

$$\beta_3 = \beta_4 = \beta_5 = 0 \quad (9)$$

2.3 Full Determination of Land Values

The full determination of land values requires completing a model for 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 workers, $k = X, Y$, where type-Y workers labor in the housing sector. Preferences are modeled by $U^k(x, y; Q_j^k)$, 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 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

⁵Non-neutral productivity differences would suggest interacting productivity shifters Z_j with input prices \hat{r}_j and \hat{m}_j in equation (6). Estimated coefficients on these estimates were found not to be statistically significant in most specifications.

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:

$$e(p_j, \bar{u}; Q^j) = m^j - \tau(m^j) \quad (10)$$

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

$$\hat{Q}_j^k = s_y^k \hat{p}_j - (1 - \tau^k) s_w \hat{w}_j^k \quad (11)$$

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 , 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 that for (3) yields the measure of tradeable productivity:

$$\hat{A}_j^X = \theta^L \hat{r}_j + \theta^N \hat{w}_j^X \quad (12)$$

where θ^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

$$\hat{A}_j^Y = \phi^L \hat{r}_j + \phi^N \hat{w}_j^Y - \hat{p}_j \quad (13)$$

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

$$\hat{A}_j \equiv s_x \hat{A}_j^X + s_y \hat{A}_j^Y \quad (14)$$

where s_x is the average expenditure share on tradeables. Combining equations (11), (12), (13), and (14) 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 federal government that depends on wages:

$$s_R \hat{r}_j = \hat{A}_j + \hat{Q}_j - \tau s_w \hat{w}_j \quad (15)$$

3 Data

We calculate our land price index from the CoStar COMPS database of commercial real estate sales. The CoStar Group is a provider of commercial real estate information that 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 “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 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

⁶We downloaded data from March through June 2011.

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

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. We controlled for 12 categories of “proposed use” for each property in addition to a category for no proposed use. 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 (a property could have more than one proposed use). We calculate a land-value 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. A major concern with this approach is that the land sales we observe are not a random sample of all land parcels. We use a geography-based weighting scheme to mitigate the potential selection bias, which we discuss in section 4.1. 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 1, are discussed in the next section.

We calculate wage and house price differentials using the 2007-2009 American Community Survey, which samples 3 percent of the population. 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 are used as 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. Housing costs are estimated from rents and imputed rents, based off of housing prices, combined so as to have a fully representative sample of the housing stock in a

⁸Again, 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.

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

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 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. 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. Just as Saiz (2010) we find that his index of topographic constraints is positively correlated with the WRLURI, with a correlation coefficient of 0.302 (s.e. = 0.080).

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

¹⁰Two 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.

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.¹¹

We restrict our analysis to metropolitan areas with at least 20 land-sale observations, that have available WRLURI, Saiz and construction wage indices, leaving 189 MSAs and PMSAs¹². These use 68,757 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 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 percent deviation of each variable from the national average.

4 Results

The main measures for the analysis are reported in table 2 for a selected number of metropolitan areas, ranked by land value, and by metropolitan size. The highest land values in the sample are in New York and San Francisco. 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 the Midwest 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 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 quickly consider the stability of our results.

¹¹The 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.

¹²of these, 183 are included in the RS Means construction cost index

4.1 Land Values

We report the results of our land value regressions in Table 1. 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 low at 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); for a summary of subsequent documentation, see Colwell and Sirmans (1993). The logic of 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. In specification 3, we add controls for quarter of sale and a number of intended-use categories. 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 not feasible to correct for possible selection bias using our dataset because we do not observe lots that are not sold¹³. One especially relevant source of selection bias in our sample is that the geographical distribution of land sales we observe may differ systematically from the distribution of land throughout the city, for instance if we are more likely to observe land sales on the urban fringe, where development activity is more intense.

In column 4, we attempt to 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

¹³There 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).

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.

4.2 Simple Model with Constraints

The land-value and housing-cost indices are plotted in figure 2. A simple linear regression produces a slope of 0.39, which, assuming all other costs are uniform across cities, is land's estimated share of costs at the average rent. The curvature in the quadratic regression yields an estimate of the elasticity of substitution of 0.95, which is not significantly different from one, and implies a very narrow range of cost shares across metro areas from 37 to 41 percent. 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.

The results in columns 1 and 2 of table 3 reveal that allowing for the elasticity of substitution between land and other inputs into the housing production function and accounting for regulatory and geographic constraints has little effect on the estimated cost-share of land, while the estimated elasticity of substitution is statistically indistinguishable from one. Moreover, a standard deviation increase in either the geographic constraint or regulatory index predicts an 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 rents are less responsive to differences in land values and constraints. The results in column 4 show the opposite holds true of estimates based on the value of owner-occupied housing alone.¹⁴ As it is not clear which measure is more representative, and the share of renters varies substantially across metro areas, we proceed with our original housing-cost measure, bearing in mind these effects.

Columns 5 and 6 of table 3 employ instrumental variables to account for the possible endogeneity of land rents. In column 5, heating degree days are employed as an instrument, while in column 6 dummies for Census divisions are also included as instruments. The estimates in column 5 are too imprecise to be useful, but are included for consistency with Tables 4A and 4B. In column 6, the cost share of land is estimated at 0.43 (s.e. 0.13), and the impacts of the geographical and regulatory constraints are estimated to be smaller at 3 percent. However, a test chi-squared test of the endogeneity of the land rents has a p-value of 0.75, suggesting we cannot reject the null hypothesis that land rents are exogenous. This result is part of a more general pattern suggesting that bias from the endogeneity of land rents is empirically unimportant in our context.

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, implying that estimates of ϕ_L without these costs are biased positively.¹⁵ 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

¹⁴Figure C plots housing values against housing rents and shows that the two are strongly correlated, although a one-percent increase in rents predicts a 1.75-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 (0.68-percent).

¹⁵These 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.

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, 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 4A 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, which passes at the usual statistical sizes. This means that, conditional on productivity, housing exhibits constant returns. According to the test, the CD formulation in column 2 also appears reasonable, with the point estimate of σ^Y implied by the estimates in column 4 statistically indistinguishable from one at 1.11. In this specification, we find a cost-share of land of 23 percent and a somewhat smaller impact of regulatory constraints, which 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 columns 6 and 7 we use the instrumental variables approach outlined in the previous section to address concerns about the possible endogeneity of land rents. The estimated cost share of land is higher in these specifications, and the effects of the geographical and regulatory constraints are lower. However, the standard errors on these estimates are relatively large, and we remain unable to reject the null hypothesis that land rents are exogenous.

Results in columns 1 through 4 of table 4B, which use construction wages, rather than costs, are quite similar. The point estimate for σ^Y is statistically indistinguishable from one at 0.95, consistent with the CD production function. The estimates in column 5 imply that a 1-percent increase in construction wages predicts a 0.65 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 17 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 employ our instrumental variable strategy to test for endogeneity in land rents. As in table 4A, the point estimates for the land share are lower than the OLS estimates, as are the impacts of the geographical and regulatory constraints. In specification 8 we can reject the null hypothesis that land rents are exogenous, but we cannot reject the null in column 9. Taken as a whole, we believe our instrumental variables strategy indicates that bias from the endogeneity of land rents is not of major importance when we control for geographic and regulatory constraints, which are the major drivers of variation in housing productivity across metro areas. However, we do note that the IV estimates of the land share are higher and estimates of the impacts of geographic and regulatory constraints are lower than those obtained by OLS.

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 5A, 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 its 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 columns 2 and 3 we report our favored estimates, using the CRS specifications from column 4 of tables 4A and 4B, but with the disaggregated regulatory subindices. 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 local political pressure, 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 we do not model. In addition, we find that the cost-share of land appears to be very close to 20 percent and that the elasticity of substitution is between 0.79 and 0.94, but is not significantly different from one. These estimates predict the cost share of land in the sample ranges between 15 and 27 percent.

In table 5B, 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. 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, the expected signs on the constituent parts are opposite the sign on the geographic constraint index. In columns 2 and 4, we report our favored estimates, the CRS specifications from column 4 of tables 4A and 4B, but with the disaggregated geographical constraint index. In columns 3 and 5, we also include the mean slope of each MSA, calculated at the PUMA level. We find that higher flat land and solid land shares lower costs, as expected, and that the impact of the flat land share is estimated to be smaller when the average slope is included, although the other estimated parameters do not change noticeably.

4.5 Productivity in Housing and Tradeables

In table 6 we provide measures of housing productivity from the empirical model in column 3 of table 5A, 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 .¹⁶ The two productivity measures are plotted against each other in Figure 4, which displays iso-productivity 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 Gary, IN and La Crosse WI-MN; Among metros with over one million inhabitants, the top five are St. Louis, Las Vegas, Pittsburgh, Buffalo, and Cleveland. The least productive metros are typically along the coasts of California and New England, with Ventura, CA, at the bottom of the list, followed by Orange County, Santa Barbara, and Danbury and Bridgeport, CT.¹⁷

The most productive city in the United States overall is New York, which has high tradeable productivity and above average 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 1.1-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

¹⁶This 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.

¹⁷These productivities are positively related to the housing supply elasticities, with a 1-point increase in productivity predicting a 2.58-point (s.e. = 0.39) increase in the supply elasticity ($R^2 = 0.30$).

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: 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 as 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 (14) and (15) 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 19 to 22 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 about 20 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 around 1, so this share varies in a relatively tight range of 0.15 to 0.27. 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 percent of income.

Housing productivity varies considerably across metro areas with a standard deviation of 0.19 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, local political pressure 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 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

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

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

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

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

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

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

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

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

may be used to identify these effects, with the restriction that $\gamma_2 = -\gamma_3$. A model imposing all of the restrictions is:

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

Note that $(\hat{A}_j^{YM} - \hat{A}_j^{YL}) = \gamma_2 / 2\beta_3$, and thus can be fully estimated off of the model.

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 gauge the stability of the estimates we present. First, we split the sample into three subsamples for 2007, 2008, and 2009. In table A5, 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 18.3 percent to 22.8 percent, while the estimated elasticity of substitution ranges from 0.166 to 1.112. 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 18.5 percent to 20.7 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 0.53 to 1.56. 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. 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.

A scatter plot showing the relationship between Unweighted Land Rent (X-axis) and Weighted Land Rent (Y-axis) for 100 cities. The X-axis ranges from -3.0 to 1.5, and the Y-axis ranges from -3.5 to 1.5. The data points are represented by circles of varying sizes, indicating the size of each city. Two regression lines are shown: a red dashed line representing the OLS regression and a purple dash-dot line representing the 2SLS regression. The 2SLS regression line is steeper than the OLS regression line, particularly for cities with negative land rents. Several cities are labeled with their abbreviations, including ROC, SYR, PVM, PHO, MOB, AUS, DEN, WVR, PIT, ROC, SEA, SFO, and NY.

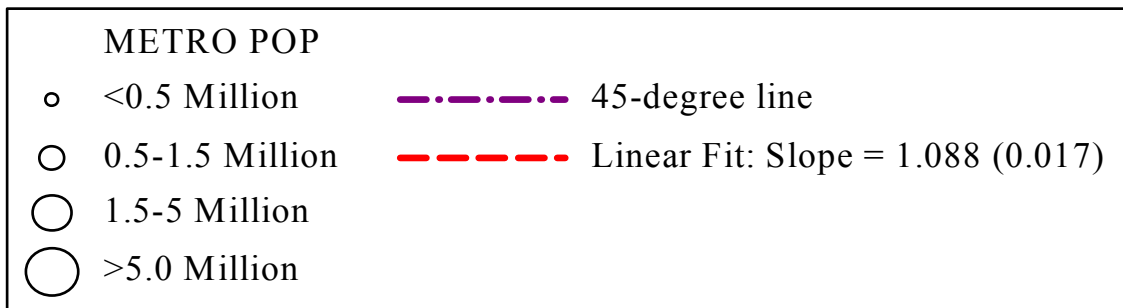


Figure 2: Housing Costs vs. Land Values

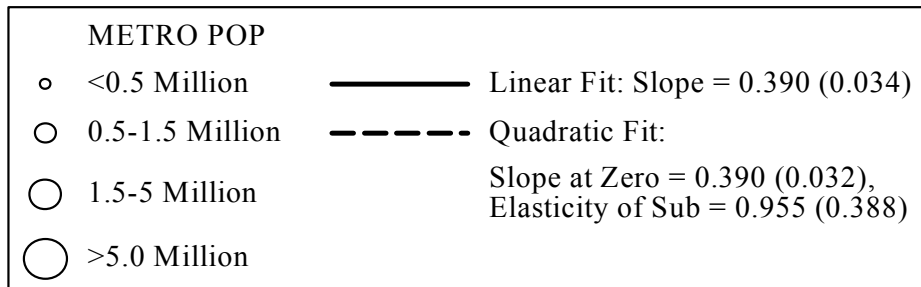
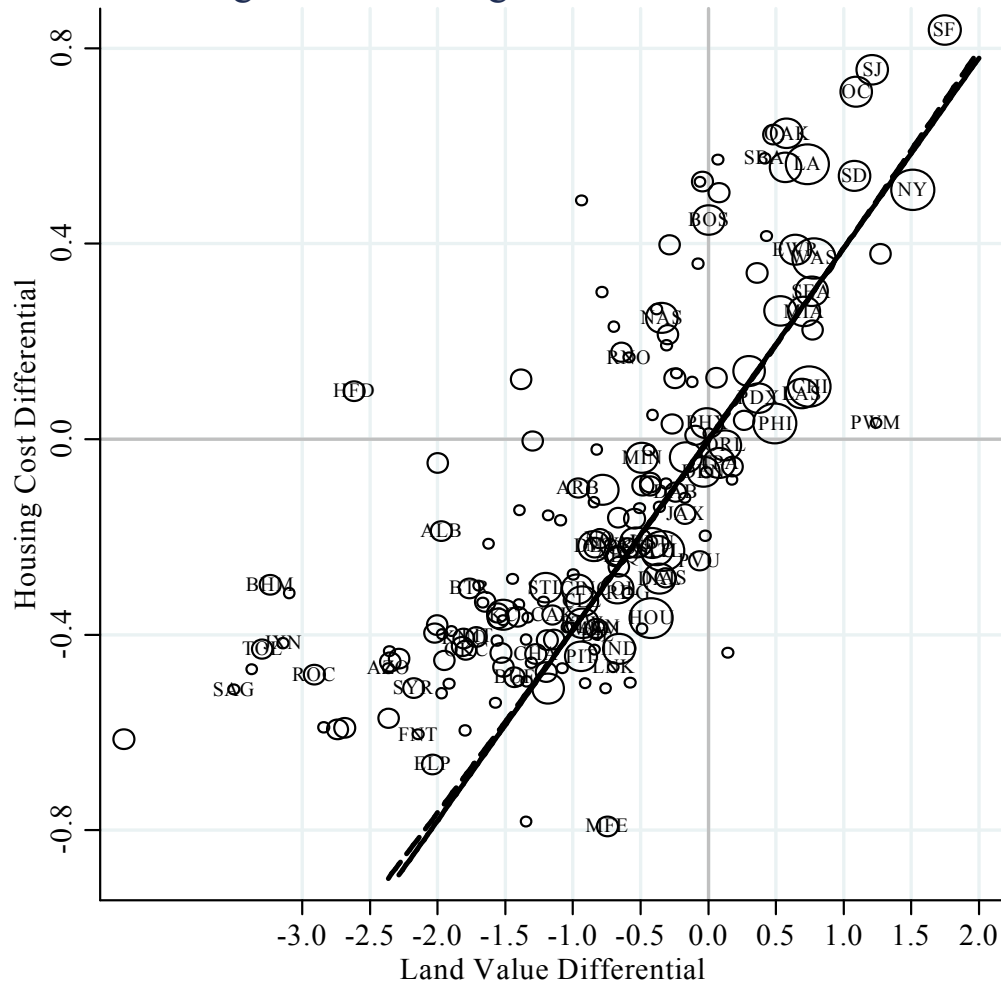
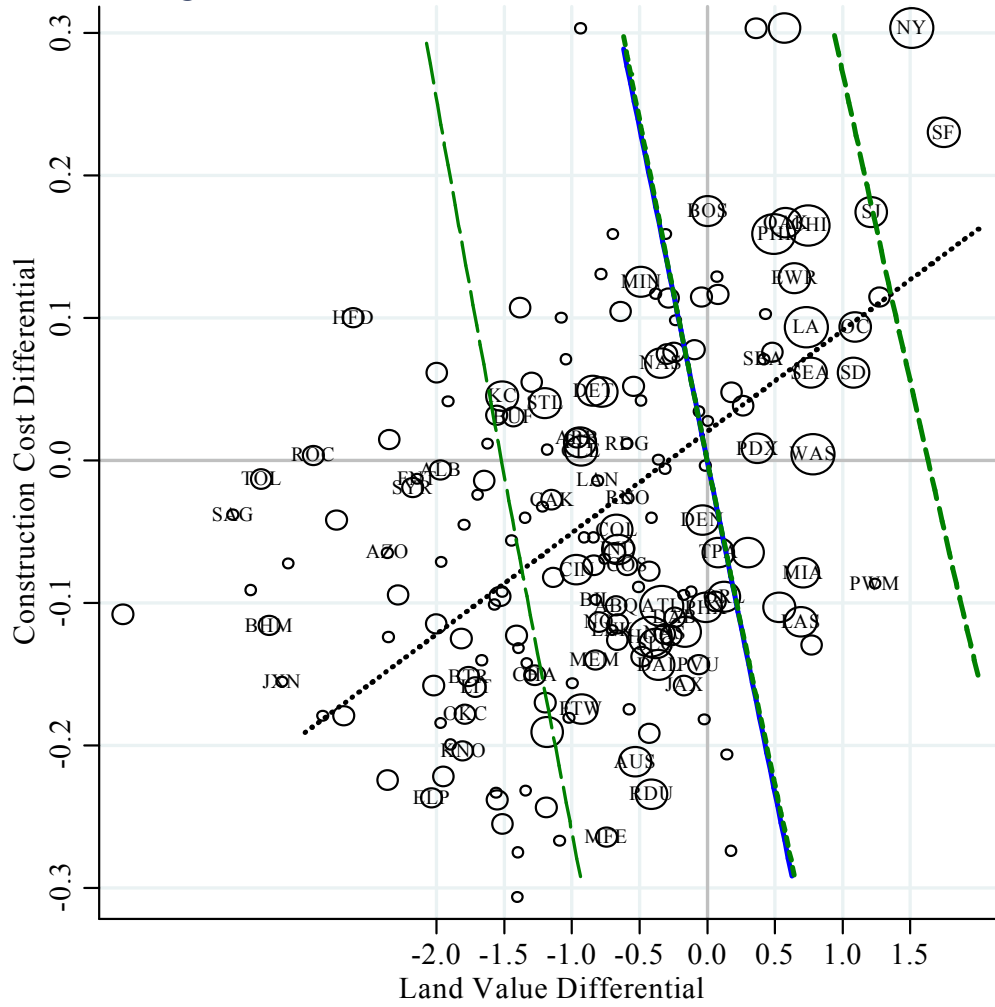
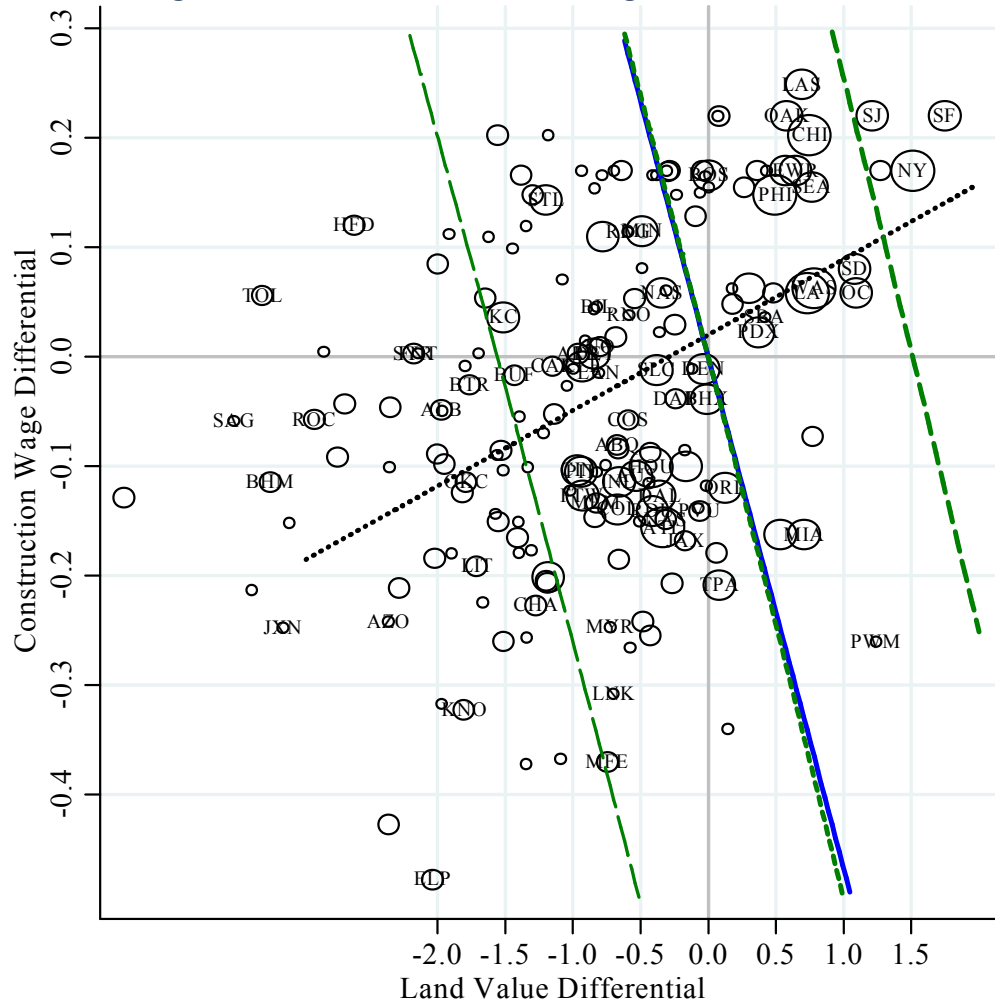


Figure 3A: Construction Costs vs. Land Values



METRO POP	Linear Fit: Slope = 0.071 (0.017)
○ <0.5 Million	—————	C-D ZPC: Land Share = 0.318 (0.044)
○ 0.5-1.5 Million	-----	CES ZPCs, cost diffs = -0.5, 0.0, 0.5
○ 1.5-5 Million	-----	Elasticity of Sub = 1.066 (0.487)
○ >5.0 Million	-----	Land Share at Zero = 0.318 (0.042)

Figure 3B: Construction Wages vs. Land Values



METRO POP	Linear Fit: Slope = 0.069 (0.011)
○ <0.5 Million	—	C-D ZPC: Land Share = 0.326 (0.040)
○ 0.5-1.5 Million	---	CES ZPCs, cost diffs = -0.5, 0.0, 0.5
○ 1.5-5 Million	---	Elasticity of Sub = 1.066 (0.487)
○ >5.0 Million	---	Land Share at Zero = 0.318 (0.042)

Figure 3C: Plot of housing costs predicted using data and basic model in 2A

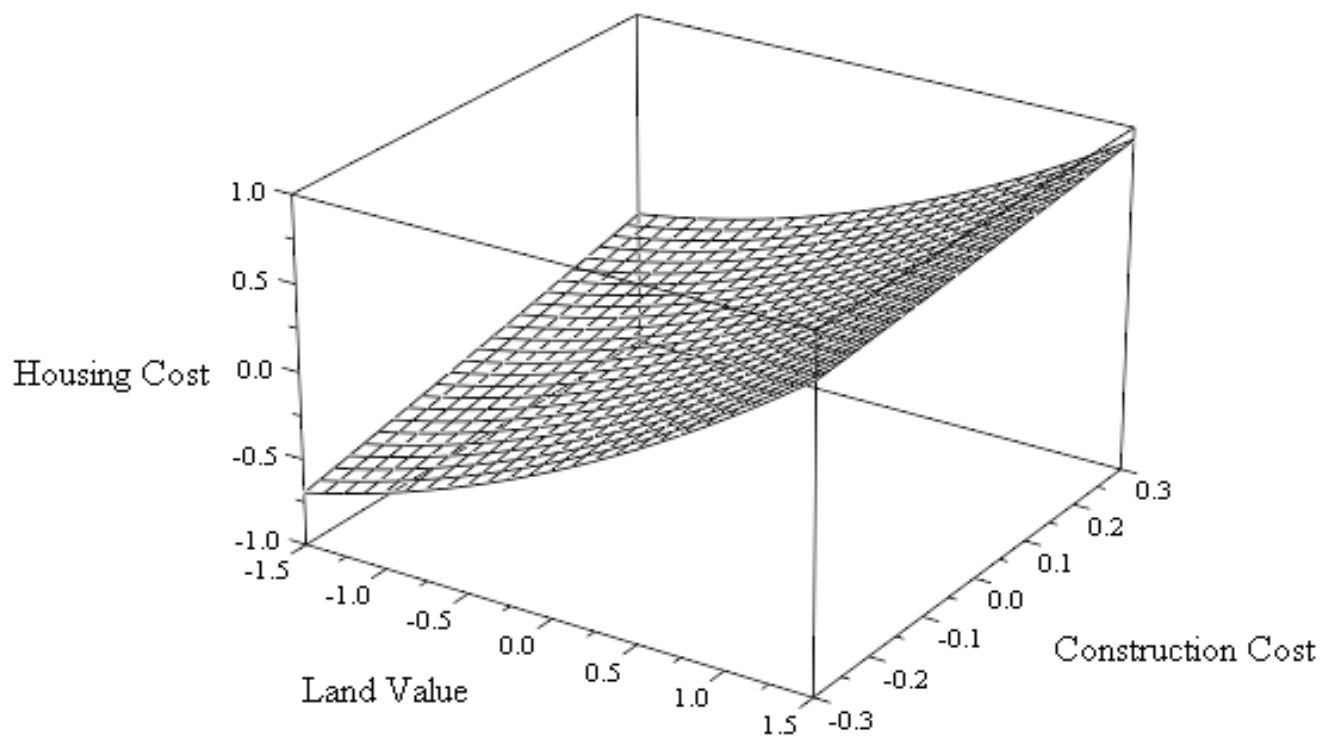
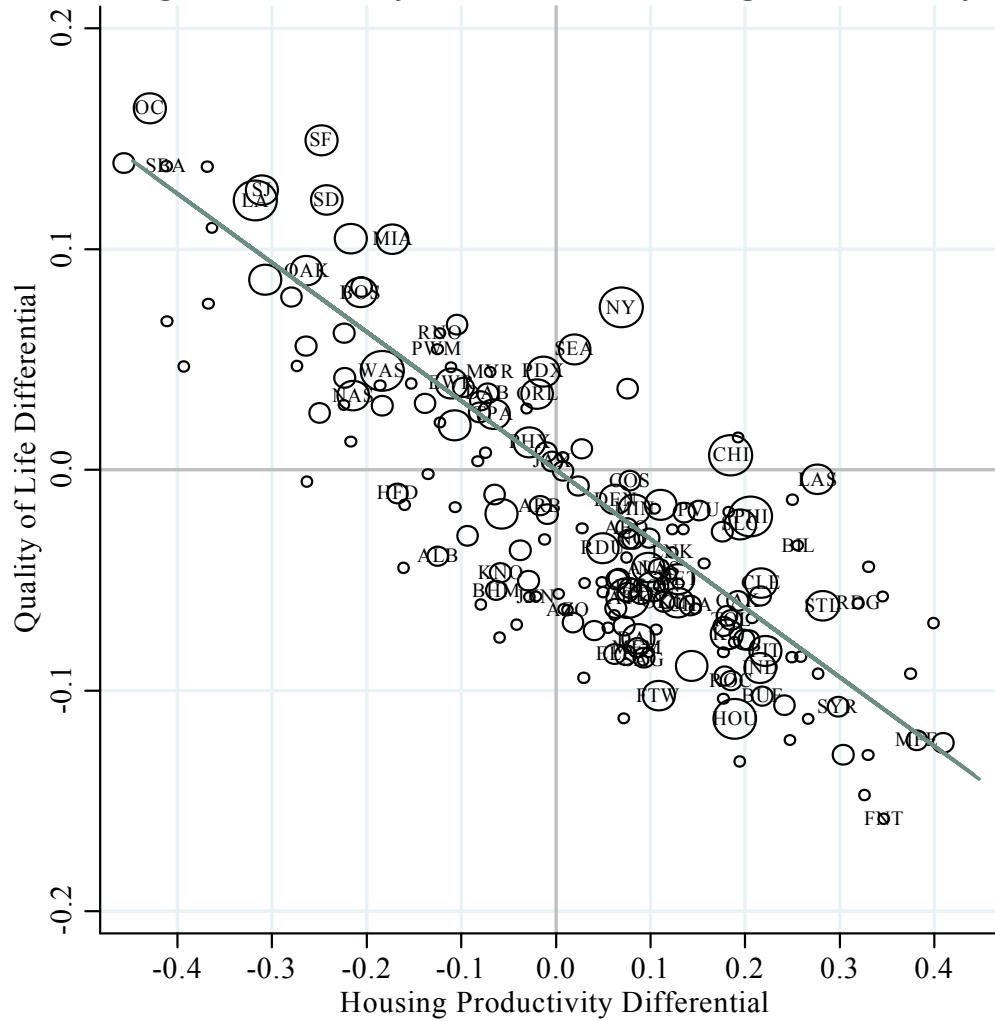


Figure 5: Quality of Life vs. Housing Productivity



METRO POP

○ <0.5 Million

○ 0.5-1.5 Million

○ 1.5-5 Million

○ >5.0 Million

— Linear Fit: Slope = -0.313 (0.028)

Figure A: Construction Costs vs. Construction Wages

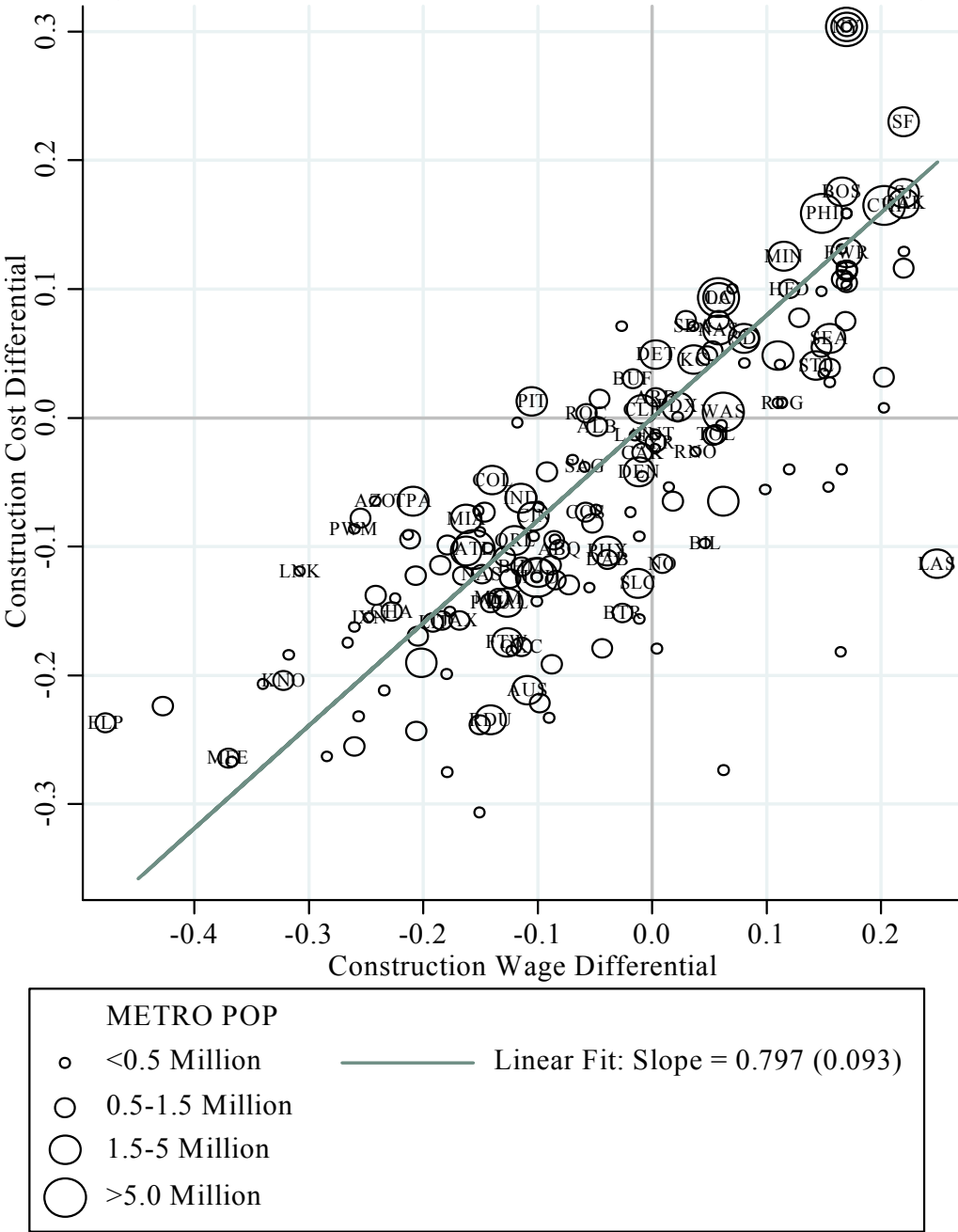
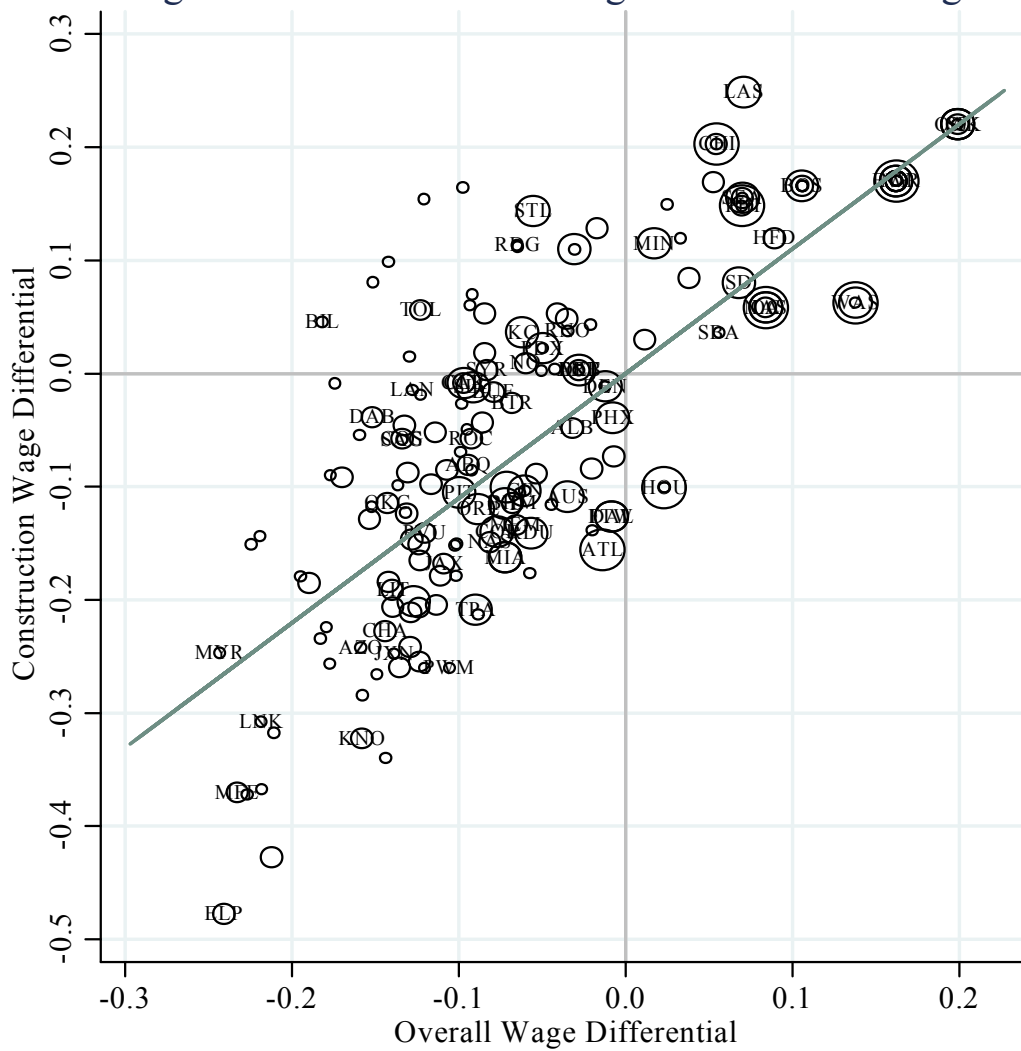


Figure B: Construction Wages vs. Overall Wages



METRO POP

○ <0.5 Million

○ 0.5-1.5 Million

○ 1.5-5 Million

○ >5.0 Million

— Linear Fit: Slope = 1.102 (0.076)

Figure C: Housing Prices vs. Housing Rents

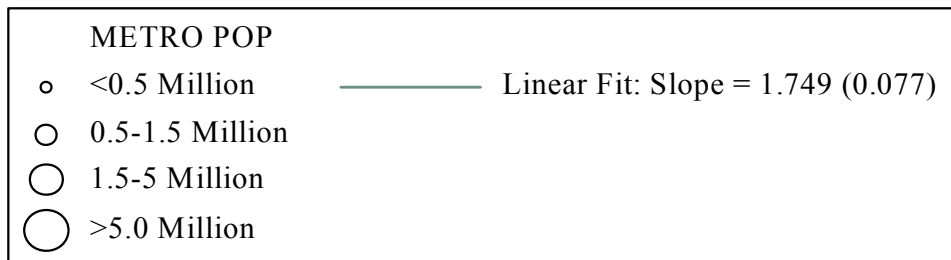
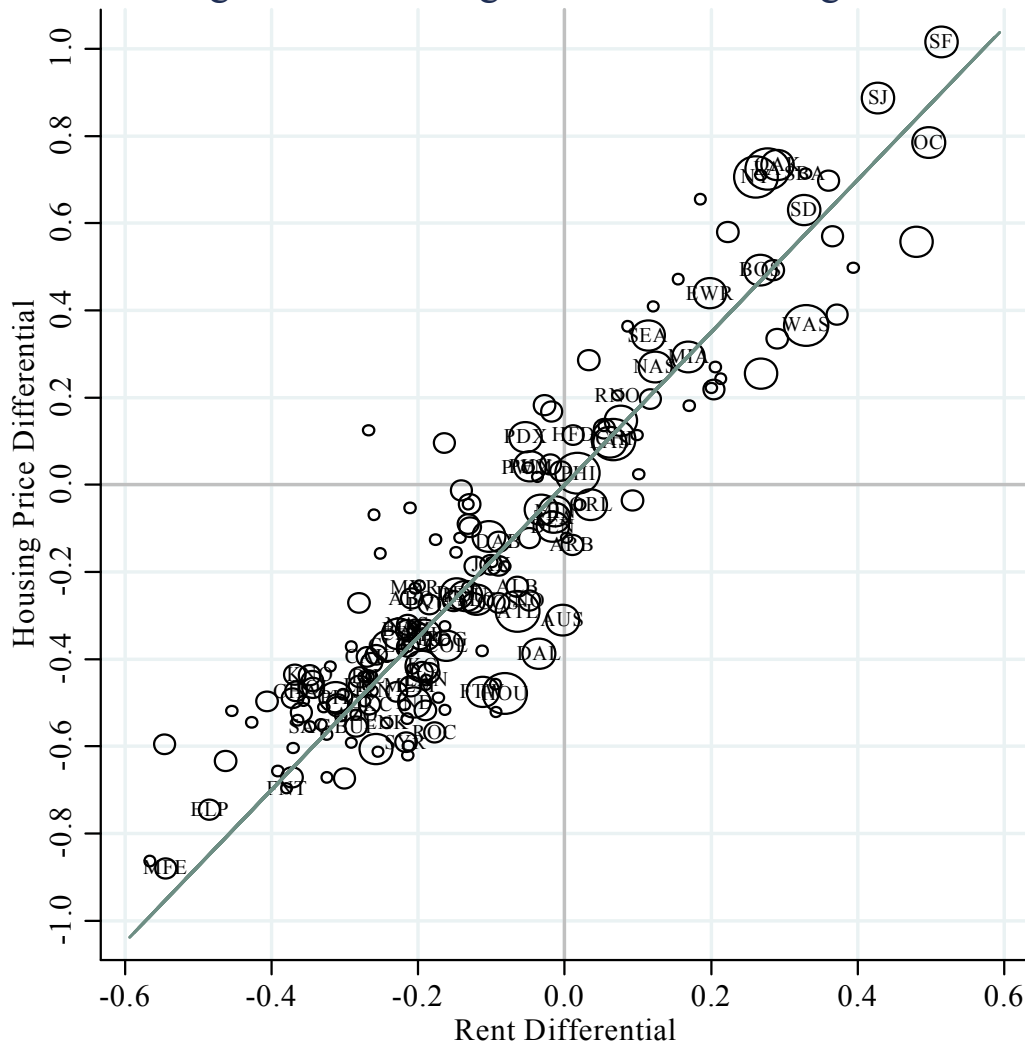


TABLE 1: LAND VALUE AUXILLIARY REGRESSION

	Dependent Variable: Log Price per Acre			
	(1)	(2)	(3)	(4)
Log lot size (acres)		-0.646 (0.012)	-0.645 (0.012)	-0.591 (0.036)
No planned use			-0.203 (0.021)	-0.341 (0.096)
Planned use: commercial			-0.387 (0.076)	-0.306 (0.091)
Planned use: industrial			-0.315 (0.029)	-0.538 (0.128)
Planned use: retail			0.269 (0.018)	0.194 (0.024)
Planned use: single family			-0.026 (0.024)	-0.182 (0.086)
Planned use: multi-family			-0.072 (0.041)	-0.163 (0.142)
Planned use: office			0.074 (0.032)	0.188 (0.077)
Planned use: apartment			0.465 (0.054)	0.344 (0.149)
Planned use: hold for development			-0.074 (0.026)	-0.117 (0.067)
Planned use: hold for investment			-0.339 (0.062)	-0.244 (0.062)
Planned use: mixed use			0.377 (0.046)	0.412 (0.079)
Planned use: medical			0.166 (0.039)	-0.079 (0.099)
Planned use: parking			0.178 (0.053)	0.206 (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			Raw Differentials			Land Value Rank
			Land Value	Housing Cost	Wages (Const. Only)	Regulation Index (z-score)	Geo Avail. Index (z-score)	Const. Cost Index	
<i>Metropolitan Areas:</i>									
New York, NY PMSA	9,747,281	1,603	1.922	0.510	0.170	0.683	0.492	0.303	1
San Francisco, CA PMSA	1,785,097	152	1.820	0.836	0.220	0.793	2.055	0.230	2
Jersey City, NJ PMSA	597,924	43	1.450	0.380	0.170	0.113	0.177	0.115	3
San Jose, CA PMSA	1,784,642	217	1.256	0.755	0.220	-0.011	1.609	0.174	4
Orange County, CA PMSA	3,026,786	233	1.092	0.711	0.058	0.207	1.068	0.094	5
Washington, DC-MD-VA-WV PMSA	5,650,154	1,840	0.677	0.370	0.062	0.318	-0.772	0.004	15
Chicago, IL PMSA	8,710,824	3,511	0.664	0.107	0.203	-0.316	0.473	0.165	17
Philadelphia, PA-NJ PMSA	5,332,822	859	0.607	0.031	0.148	1.341	-0.953	0.159	18
Boston, MA-NH PMSA	3,552,421	122	0.566	0.448	0.166	2.230	0.181	0.175	22
Phoenix-Mesa, AZ MSA	4,364,094	5,946	0.216	0.032	-0.039	0.658	-0.772	-0.103	35
Riverside-San Bernardino, CA PMSA	4,143,113	2,452	-0.007	0.248	0.058	0.483	0.372	0.068	45
Atlanta, GA MSA	5,315,841	5,229	-0.090	-0.229	-0.156	-0.286	-1.243	-0.102	53
Detroit, MI PMSA	4,373,040	679	-0.403	-0.218	0.003	-0.264	-0.267	0.049	80
Houston, TX PMSA	5,219,317	1,143	-0.426	-0.366	-0.101	-0.936	-1.037	-0.124	83
Dallas, TX PMSA	4,399,895	811	-0.427	-0.286	-0.127	-0.699	-1.001	-0.144	85
Macon, GA MSA	356,873	20	-1.819	-0.498	-0.266	-1.643	-1.061	-0.175	185
Youngstown-Warren, OH MSA	554,614	49	-1.850	-0.593	-0.092	-0.932	-0.936	-0.042	186
Glens Falls, NY MSA	128,774	21	-1.915	-0.315	-0.152	-2.836	0.514	-0.072	187
Evansville-Henderson, IN-KY MSA	305,455	33	-2.083	-0.482	-0.019	-1.965	-1.024	-0.073	188
Saginaw-Bay City-Midland, MI MSA	390,032	41	-2.087	-0.512	-0.059	-0.354	-0.655	-0.038	189
<i>Population Categories:</i>									
Less than 500,000	25,078,538	4,642	-0.741	-0.219	-0.045	-0.272	-0.061	-0.059	4
500,000 to 1,500,000	55,777,644	13,942	-0.573	-0.193	-0.059	-0.259	-0.207	-0.063	3
1,500,000 to 5,000,000	89,173,333	32,032	0.150	0.058	0.014	0.116	0.117	0.002	2
5,000,000+	49,824,250	15,945	0.765	0.212	0.076	0.209	-0.041	0.100	1
United States		29,671	0.853	0.375	0.146	1.003	0.995	0.142	
		<i>total</i>				<i>standard deviations (population weighted)</i>			

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

Specification	Basic Cobb-Douglas	CES	Rents Only	Housing Prices	IV for Land-Value Diff.	IV for Land-Value Diff.
Dependent Variable	Hous. Cost	Hous. Cost	Hous. Rent	Hous. Price	Hous. Cost	Hous. Cost
	(1)	(2)	(3)	(4)	(5)	(6)
Land-Value Differential	0.285 (0.035)	0.280 (0.035)	0.185 (0.027)	0.327 (0.037)	-0.334 (1.469)	0.433 (0.131)
Land-Value Differential Squared		0.020 (0.032)	-0.001 (0.025)	0.048 (0.032)		
Geographic Constraint Index: z-score	0.084 (0.026)	0.083 (0.028)	0.035 (0.019)	0.099 (0.032)	0.307 (0.529)	0.031 (0.048)
Regulatory Index: z-score	0.081 (0.020)	0.085 (0.016)	0.043 (0.014)	0.098 (0.018)	0.289 (0.501)	0.031 (0.046)
Constant	0.000 (0.023)	-0.014 (0.037)	0.001 (0.028)	-0.034 (0.041)	0.000 (0.060)	0.000 (0.020)
Number of Observations	189	189	189	189	189	189
Adjusted R-squared	0.828	0.829	0.741	0.840	0.114	0.767
Elasticity of Substitution	1.000	0.804 (0.312)	1.019 (0.329)	0.563 (0.279)	1.000	1.000
First-stage F-statistic					43.997	33.394
p-value for chi-square test of Land-Value endogeneity					0.326	0.745

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 2. Columns (1), (2), and (5) use both renter and owner observations, column (3) uses renters only, and column (4) uses owners only. Instruments in column 5 are average heating degree days; instruments in column 6 are heating degree days and Census division dummies. Test of regressor endogeneity is from Baum et al. (2007).

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

Specification Dependent Variable	Basic Cobb- Douglas Hous. Cost (1)	Restricted Cobb- Douglas Hous. Cost (2)	Translog Hous. Cost (3)	Restricted Translog Hous. Cost (4)	Non-neutral Productivity Translog Hous. Cost (5)	IV for Land- Value Diff. Hous. Cost (6)	IV for Land- Value Diff. Hous. Cost (7)
Land-Value Differential	0.236 (0.043)	0.226 (0.047)	0.248 (0.041)	0.226 (0.044)	0.222 (0.044)	0.429 (0.130)	0.376 (0.114)
Construction-Cost Differential	0.582 (0.132)	0.774 (0.047)	0.588 (0.206)	0.774 (0.044)	0.778 (0.044)	0.571 (0.130)	0.624 (0.114)
Land-Value Differential Squared			0.015 (0.034)	-0.010 (0.039)	-0.036 (0.042)		
Construction-Cost Differential Squared			-0.271 (1.279)	-0.010 (0.039)	-0.036 (0.042)		
Land-Value Differential X Construction-Cost Differential			-0.154 (0.286)	0.020 (0.078)	0.072 (1.077)		
Geographic Constraint Index: z-score	0.085 (0.026)	0.082 (0.026)	0.080 (0.026)	0.084 (0.028)	0.080 (0.026)	0.015 (0.050)	0.032 (0.042)
Regulatory Index: z-score	0.061 (0.018)	0.053 (0.016)	0.058 (0.016)	0.051 (0.015)	0.057 (0.017)	-0.003 (0.036)	0.011 (0.030)
Geographic Constraint Index times Land Value Differential minus Construction Cost Differential					0.043 (0.036)		
Regulatory Index times Land Value Differential minus Construction Cost Differential					0.014 (0.025)		
Constant	0.001 (0.022)	0.001 (0.023)	0.007 (0.041)	0.007 (0.033)	-0.001 (0.032)	0.000 (0.023)	0.000 (0.022)
Number of Observations	183	183	183	183	183	183	183
Adjusted R-squared	0.854	0.852	0.854	0.852	0.763	0.594	0.668
<i>p</i> -value for constant-returns-to-scale restrictions		0.154		0.694			
<i>p</i> -value for Cobb-Douglas restrictions	0.732	0.149					
<i>p</i> -value for all restrictions		0.465					
Elasticity of Substitution	1.000	1.000		1.112 (0.462)		1.000	1.000
First-stage F-statistic						43.852	30.838
<i>p</i> -value for chi-square test of Land-Value endogeneity						0.106	0.352

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). Instruments in column 6 are average heating degree days; instruments in column 7 are heating degree days and Census division dummies. Test of regressor endogeneity is from Baum et al. (2007).

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	IV for Land-Value Diff.	IV for Land-Value Diff.
Dependent Variable	Hous. Cost (1)	Hous. Cost (2)	Hous. Cost (3)	Hous. Cost (4)	Const. Cost (5)	Hous. Cost (6)	Hous. Cost (7)	Hous. Cost (8)	Hous. Cost (9)
Land-Value Differential	0.238 (0.039)	0.229 (0.039)	0.231 (0.043)	0.228 (0.038)	0.030 (0.016)	0.240 (0.037)	0.222 (0.035)	0.477 (0.136)	0.376 (0.114)
Construction-Wage Differential	0.560 (0.155)	0.771 (0.039)	0.508 (0.212)	0.772 (0.038)	0.649 (0.064)	0.536 (0.018)	0.778 (0.035)	0.523 (0.136)	0.624 (0.114)
Implied Capital-Cost Differential	0.201 (0.141)	0.000	0.261 (0.111)	0.000	0.271 (0.049)	0.224 (0.011)	0.000	0.000	0.000
Land-Value Differential Squared			-0.003 (0.032)	0.005 (0.030)			-0.031 (.028)		
Construction-Wage Differential Squared			-1.196 (1.051)	0.005 (0.030)			-0.031 (.028)		
Land-Value Differential X Construction-Wage Differential			0.253 (0.155)	-0.010 (0.060)			0.062 (0.056)		
Geographic Constraint Index: z-score	0.087 (0.023)	0.085 (0.023)	0.093 (0.025)	0.085 (0.025)	0.003 (0.008)	0.087 (0.024)	0.081 (0.022)	0.002 (0.055)	0.036 (0.043)
Regulatory Index: z-score	0.065 (0.018)	0.057 (0.018)	0.070 (0.016)	0.057 (0.017)	0.015 (0.011)	0.066 (0.018)	0.066 (0.020)	-0.013 (0.038)	0.015 (0.030)
Geographic Constraint Index times Land Value Differential minus Construction Cost Differential							0.023 (0.029)		
Regulatory Index times Land Value Differential minus Construction Cost Differential							0.056 (0.030)		
Constant	0.000 (0.023)	0.000 (0.023)	0.010 (0.038)	-0.003 (0.032)	-0.001 (0.010)	0.000 (0.023)	-0.014 (0.031)	0.000 (0.024)	0.000 (0.022)
Number of Observations	189	189	189	189	183	189	189	189	189
Adjusted R-squared	0.859	0.855	0.861	0.854	0.731	0.859	0.784	0.538	0.692
<i>p</i> -value for constant-returns-to-scale restrictions		0.155		0.071		0.622			
<i>p</i> -value for Cobb-Douglas restrictions	0.429	0.875							
<i>p</i> -value for all restrictions		0.116							
Elasticity of Substitution	1.000	1.000		0.946 (0.341)	1.000			1.000	1.000
First-stage F-statistic								40.403	48.926
<i>p</i> -value for chi-square test of Land-Value endogeneity								0.036	0.314

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). Instruments in column 7 are average heating degree days; instruments in column 8 are heating degree days and Census division dummies. Test of regressor endogeneity is from Baum et al. (2007).

TABLE 5A: MODEL OF HOUSING COSTS WITH DISAGGREGATED REGULATORY INDICE

Specification	Factor Loading	Reg Index	Restricted Translog w Cons Cost	Restricted Translog w Wage Cost
Dependent Variable		(1)	Hous. Cost (2)	Hous. Cost (3)
Land-Value Differential			0.202 (0.029)	0.209 (0.032)
Land-Value Differential Squared			0.005 (0.024)	0.018 (0.022)
Geographic Constraint Index: z-score			0.059 (0.023)	0.068 (0.022)
Approval Delay: z-score	0.29	0.505 (0.033)	0.047 (0.042)	0.026 (0.038)
Local Political Pressure: z-score	0.22	0.196 (0.059)	0.038 (0.027)	0.041 (0.028)
State Political Involvement: z-score	0.22	0.386 (0.021)	0.068 (0.018)	0.059 (0.021)
Open Space: z-score	0.18	0.020 (0.013)	-0.002 (0.007)	-0.008 (0.007)
Exactions: z-score	0.15	-0.027 (0.065)	0.011 (0.050)	0.030 (0.056)
Local Project Approval: z-score	0.15	0.215 (0.017)	-0.014 (0.013)	0.007 (0.013)
Local Assembly: z-score	0.14	0.152 (0.044)	-0.011 (0.024)	-0.020 (0.026)
Density Restrictions: z-score	0.09	0.086 (0.064)	-0.022 (0.042)	-0.050 (0.043)
Supply Restrictions: z-score	0.02	0.130 (0.011)	0.009 (0.010)	0.003 (0.011)
State Court Involvement: z-score	-0.03	-0.137 (0.019)	0.063 (0.015)	0.049 (0.016)
Local Zoning Approval: z-score	-0.04	-0.094 (0.066)	-0.017 (0.042)	0.019 (0.040)
Constant		0.000 (0.019)	-0.001 (0.026)	-0.010 (0.026)
Number of Observations		189	183	189
Adjusted R-squared		0.946	0.888	0.878
Elasticity of Substitution			0.942 (0.294)	0.786 (0.259)

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 2; constituent components of Wharton Residential Land Use Regulatory Index (WRLURI) from Gyourko et al (2008).

TABLE 5B: MODEL OF HOUSING COSTS WITH DISAGGREGATED GEOGRAPHICAL INDICES

Specification		Restricted Translog w Cons Cost	Restricted Translog w Cons Cost	Restricted Translog w Wage Cost	Restricted Translog w Wage Cost
Dependent Variable	Geo Index	Hous. Cost	Hous. Cost	Hous. Cost	Hous. Cost
	(1)	(2)	(3)	(4)	(5)
Land-Value Differential		0.225 (0.029)	0.218 (0.032)	0.228 (0.036)	0.216 (0.033)
Land-Value Differential Squared		0.005 (0.024)	0.018 (0.022)	0.004 (0.031)	0.002 (0.027)
Regulatory Index: z-score		0.050 (0.016)	0.057 (0.016)	0.055 (0.018)	0.066 (0.018)
Flat Land Share: z-score	-0.506 (0.036)	-0.086 (0.023)	-0.130 (0.036)	-0.079 (0.024)	-0.147 (0.033)
Solid Land Share: z-score	-0.769 (0.055)	-0.041 (0.027)	-0.035 (0.028)	-0.048 (0.028)	-0.038 (0.028)
Mean Slope			-0.036 (0.018)		-0.055 (0.017)
Constant	0.000 (0.039)	0.008 (0.030)	0.008 (0.030)	-0.003 (0.031)	-0.001 (0.029)
Number of Observations	189	183	183	189	189
Adjusted R-squared	0.853	0.854	0.854	0.848	0.852
Elasticity of Substitution		1.135 (0.440)	1.146 (0.428)	0.952 (0.345)	0.974 (0.319)

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 2; constituent components of geographical index provided to the authors by Albert Saiz. Mean Slope based on authors' calculations.

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

AMENITY VALUE					
	<i>Productivity</i>				
	Housing (Including	Unexplained Housing		Quality of	Total
Name	Indices)	Component	Tradeables	Life	Amenity Value
<i>Metropolitan Areas:</i>					
San Francisco, CA PMSA	-0.248	0.058	0.186	0.149	0.216
New York, NY PMSA	0.069	0.092	0.165	0.073	0.193
San Jose, CA PMSA	-0.311	-0.143	0.172	0.127	0.171
Jersey City, NJ PMSA	0.076	0.111	0.153	0.037	0.151
Oakland, CA PMSA	-0.263	-0.029	0.163	0.090	0.139
Washington, DC-MD-VA-WV PMSA	-0.183	-0.196	0.133	0.045	0.091
Boston, MA-NH PMSA	-0.206	-0.013	0.079	0.080	0.087
Chicago, IL PMSA	0.185	0.125	0.025	0.007	0.062
Philadelphia, PA-NJ PMSA	0.205	0.151	0.050	-0.021	0.054
Riverside-San Bernardino, CA PMSA	-0.214	-0.069	0.066	0.034	0.031
Phoenix-Mesa, AZ MSA	-0.028	0.046	0.006	0.012	0.011
Atlanta, GA MSA	0.076	-0.008	0.017	-0.058	-0.031
Detroit, MI PMSA	0.129	0.127	-0.037	-0.049	-0.046
Houston, TX PMSA	0.189	0.018	0.032	-0.113	-0.052
Dallas, TX PMSA	0.087	-0.071	0.008	-0.077	-0.053
Evansville-Henderson, IN-KY MSA	0.098	-0.031	-0.163	-0.083	-0.166
El Paso, TX MSA	0.062	-0.045	-0.152	-0.084	-0.167
Macon, GA MSA	-0.059	-0.173	-0.129	-0.076	-0.171
Saginaw-Bay City-Midland, MI MSA	0.092	0.054	-0.165	-0.086	-0.173
Youngstown-Warren, OH MSA	0.179	-0.068	-0.186	-0.094	-0.175
<i>Population Categories:</i>					
Less than 500,000	0.040	0.013	-0.069	-0.032	-0.067
500,000 to 1,500,000	0.038	-0.003	-0.057	-0.029	-0.057
1,500,000 to 5,000,000	-0.022	0.002	0.008	0.008	0.009
5,000,000+	-0.003	0.001	0.075	0.023	0.070
United States	0.187	0.127	0.094	0.072	0.094
<i>standard deviations (population weighted)</i>					

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)
<i>Panel A: Population</i>				
Log of Population	0.062 (0.005)	-0.059 (0.023)	-0.028 (0.015)	0.027 (0.006)
Number of Observations	189	189	189	189
Adjusted R-squared	0.709	0.152	0.058	0.468
<i>Panel B: Population Density</i>				
Weighted Density Differential	0.064 (0.004)	-0.042 (0.030)	-0.012 (0.019)	0.032 (0.006)
Number of Observations	189	189	189	189
Adjusted R-squared	0.467	0.044	0.001	0.406

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 2. 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)
<i>Panel A: Population</i>				
Housing Productivity	-0.178 (0.040)	-0.185 (0.022)	-0.222 (0.037)	-0.189 (0.030)
Natural Controls	X	X	X	X
Artificial Controls		X		X
Number of Observations	183	183	183	183
Adjusted R-squared	0.82	0.90	0.78	0.85

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 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

Full Name	Population	Cen- sus Div- ision	Obs. Land Sales	Adjusted Differentials				Raw Differentials			Productivity			Land Value Rank	
				Land Value (No Wts.)	Housing Cost	Wages (All)	Wages (Const. Only)	Geo Avail. Index (z-score)	Const. Cost Index	Tradea- bles					
Metropolitan Areas:															
New York, NY PMSA	9,747,281	2	1,603	1.922	1.529	0.510	0.162	0.170	0.683	0.492	0.303	0.069	0.165	1	
San Francisco, CA PMSA	1,785,097	9	152	1.820	1.447	0.836	0.199	0.220	0.793	2.055	0.230	-0.248	0.186	2	
Jersey City, NJ PMSA	597,924	2	43	1.450	1.487	0.380	0.162	0.170	0.113	0.177	0.115	0.076	0.153	3	
San Jose, CA PMSA	1,784,642	9	217	1.256	1.247	0.755	0.199	0.220	-0.011	1.609	0.174	-0.311	0.172	4	
Orange County, CA PMSA	3,026,786	9	233	1.092	1.204	0.711	0.084	0.058	0.207	1.068	0.094	-0.429	0.094	5	
San Diego, CA MSA	3,053,793	9	957	1.087	0.862	0.539	0.068	0.080	0.289	1.591	0.062	-0.242	0.074	6	
Miami, FL PMSA	2,500,625	5	1,233	0.980	0.926	0.261	-0.072	-0.162	1.135	2.222	-0.079	-0.172	-0.009	7	
Seattle-Bellevue-Everett, WA PMSA	2,692,066	9	1,626	0.951	0.828	0.302	0.070	0.155	1.042	0.646	0.062	0.020	0.057	8	
Los Angeles-Long Beach, CA PMSA	9,848,011	9	1,760	0.937	0.972	0.562	0.084	0.058	0.400	1.068	0.094	-0.318	0.090	9	
Oakland, CA PMSA	2,532,756	9	132	0.912	0.848	0.626	0.199	0.220	0.628	1.507	0.167	-0.263	0.163	10	
Las Vegas, NV-AZ MSA	2,141,893	8	2,553	0.849	0.856	0.093	0.071	0.249	-1.414	0.094	-0.114	0.277	0.035	11	
West Palm Beach-Boca Raton, FL MSA	1,279,950	5	321	0.828	0.776	0.223	-0.007	-0.073	0.107	1.619	-0.130	-0.104	0.029	12	
Fort Lauderdale, FL PMSA	1,766,476	5	741	0.805	0.871	0.262	-0.072	-0.162	0.786	2.178	-0.103	-0.217	-0.013	13	
Newark, NJ PMSA	2,045,344	2	142	0.712	0.364	0.388	0.162	0.170	0.720	0.019	0.128	-0.110	0.134	14	
Washington, DC-MD-VA-WV PMSA	5,650,154	5	1,840	0.677	0.674	0.370	0.138	0.062	0.318	-0.772	0.004	-0.183	0.133	15	
Santa Barbara-Santa Maria-Lompoc, CA MSA	407,057	9	29	0.665	0.707	0.575	0.056	0.036	1.022	2.670	0.071	-0.412	0.062	16	
Chicago, IL PMSA	8,710,824	3	3,511	0.664	0.262	0.107	0.055	0.203	-0.316	0.473	0.165	0.185	0.025	17	
Philadelphia, PA-NJ PMSA	5,332,822	2	859	0.607	0.132	0.031	0.070	0.148	1.341	-0.953	0.159	0.205	0.050	18	
Ventura, CA PMSA	802,983	9	131	0.605	0.717	0.623	0.084	0.058	1.542	2.366	0.076	-0.457	0.082	19	
Nassau-Suffolk, NY PMSA	2,875,904	2	396	0.583	0.674	0.556	0.162	0.170	0.761	0.492	0.303	-0.307	0.131	20	
Bergen-Passaic, NJ PMSA	1,387,028	2	79	0.577	0.717	0.527	0.162	0.170	0.706	0.492	0.115	-0.279	0.131	21	
Boston, MA-NH PMSA	3,552,421	1	122	0.566	0.482	0.448	0.106	0.166	2.230	0.181	0.175	-0.206	0.079	22	
Portland, ME MSA	256,178	1	25	0.540	-0.962	0.033	-0.105	-0.260	1.700	0.924	-0.087	-0.125	-0.031	23	
Naples, FL MSA	318,537	5	78	0.519	0.503	0.359	-0.020	-0.139	0.114	2.174		-0.363	0.023	24	
Vallejo-Fairfield-Napa, CA PMSA	541,884	9	146	0.365	0.400	0.504	0.199	0.220	1.165	0.910	0.116	-0.264	0.149	25	
Orlando, FL MSA	2,082,421	5	1,612	0.331	0.388	-0.013	-0.088	-0.120	0.156	0.287	-0.095	-0.020	-0.049	26	
Sarasota-Bradenton, FL MSA	688,126	5	601	0.325	0.382	0.126	-0.111	-0.179	1.099	1.744	-0.099	-0.205	-0.058	27	
Madison, WI MSA	491,357	3	239	0.305	-0.328	-0.090	-0.093	0.060	0.293	-0.896	-0.006	0.193	-0.092	28	
Tacoma, WA PMSA	796,836	9	539	0.295	0.386	0.039	0.070	0.155	1.868	0.314	0.038	0.136	0.041	29	
Portland-Vancouver, OR-WA PMSA	2,230,947	9	1,191	0.294	0.372	0.083	-0.049	0.022	0.080	0.355	0.009	-0.013	-0.044	30	
Tampa-St. Petersburg-Clearwater, FL MSA	2,747,272	5	1,220	0.275	0.316	-0.048	-0.090	-0.209	-0.677	0.551	-0.065	-0.066	-0.033	31	
Hagerstown, MD PMSA	145,910	5	28	0.259	-0.477	-0.084	0.138	0.062	0.182	-0.543	-0.274	0.177	0.122	32	
San Luis Obispo-Atascadero-Paso Robles, CA MSA	266,971	9	43	0.241	0.285	0.527	0.025	0.150	1.400	1.706	0.034	-0.368	-0.002	33	
Middlesex-Somerset-Hunterdon, NJ PMSA	1,247,641	2	101	0.238	0.402	0.397	0.162	0.170	1.413	0.492	0.114	-0.223	0.122	34	
Phoenix-Mesa, AZ MSA	4,364,094	8	5,946	0.216	0.358	0.032	-0.008	-0.039	0.658	-0.772	-0.103	-0.028	0.006	35	
New Haven-Meriden, CT PMSA	558,692	1	43	0.210	-0.152	0.177	0.162	0.170	-0.330	0.712	0.105	-0.009	0.122	36	
Baltimore, MD PMSA	2,690,886	5	802	0.207	0.198	0.140	0.138	0.062	2.139	-0.393	-0.065	-0.057	0.121	37	
Santa Rosa, CA PMSA	472,102	9	153	0.197	0.534	0.572	0.199	0.220	1.726	1.571	0.129	-0.367	0.145	38	
Melbourne-Titusville-Palm Bay, FL MSA	536,357	5	420	0.154	0.142	-0.096	-0.124	-0.255	0.473	1.631	-0.078	-0.081	-0.058	39	
Lawrence, MA-NH PMSA	413,626	1	29	0.136	-0.178	0.302	0.106	0.166	1.967	0.181	0.131	-0.152	0.068	40	
Reno, NV MSA	414,820	8	57	0.119	0.096	0.167	-0.035	0.038	-0.813	1.238	-0.026	-0.122	-0.037	41	
Provo-Orem, UT MSA	545,307	8	47	0.108	0.168	-0.250	-0.120	-0.141	-0.012	1.408	-0.144	0.151	-0.081	42	
Olympia, WA PMSA	250,979	9	250	0.107	0.067	0.011	0.070	0.155	0.558	0.400	0.027	0.123	0.036	43	
Denver, CO PMSA	2,445,781	8	2,015	0.076	-0.060	-0.067	-0.012	-0.011	0.996	-0.639	-0.042	0.063	-0.007	44	
Riverside-San Bernardino, CA PMSA	4,143,113	9	2,452	-0.007	0.102	0.248	0.084	0.058	0.483	0.372	0.068	-0.214	0.066	45	
Stockton-Lodi, CA MSA	674,860	9	163	-0.039	0.115	0.214	0.053	0.169	0.582	-0.863	0.075	-0.098	0.013	46	
Wilmington-Newark, DE-MD PMSA	635,430	5	107	-0.059	0.008	-0.004	0.070	0.148	0.392	-0.738	0.055	0.099	0.033	47	
Jacksonville, FL MSA	1,301,808	5	793	-0.062	0.132	-0.153	-0.109	-0.168	-0.371	0.822	-0.158	-0.004	-0.068	48	
Salt Lake City-Ogden, UT MSA	1,567,650	8	145	-0.062	0.077	-0.228	-0.091	-0.012	-0.384	2.001	-0.128	0.195	-0.085	49	
Austin-San Marcos, TX MSA	1,705,075	7	384	-0.081	-0.382	-0.211	-0.035	-0.109	-0.778	-1.258	-0.212	0.097	-0.012	50	
Visalia-Tulare-Porterville, CA MSA	429,668	9	32	-0.088	-0.271	-0.129	-0.021	0.043	0.377	-0.510		0.135	-0.031	51	
Allentown-Bethlehem-Easton, PA MSA	706,374	2	85	-0.088	0.038	-0.162	-0.041	0.053	-0.305	-0.442	0.052	0.176	-0.052	52	
Atlanta, GA MSA	5,315,841	5	5,229	-0.090	-0.100	-0.229	-0.014	-0.156	-0.286	-1.243	-0.102	0.076	0.017	53	

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

	Full Name	Population	Cen- sus Div- ision	Obs. Land Sales	Adjusted Differentials				Raw Differentials			Productivity			
					Land Value (No Wts.)	Housing Cost	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Avail. Index (z-score)	Const. Cost Index	Housing	Tradea- bles	Land Value Rank	
	Trenton, NJ PMSA	366,222	2	35	-0.091	0.254	0.241	0.162	0.170	2.395	-0.875	0.110	-0.135	0.114	54
	Fort Myers-Cape Coral, FL MSA	586,908	5	294	-0.092	0.098	0.031	-0.124	-0.207	-0.569	1.101	-0.123	-0.224	-0.075	55
	Modesto, CA MSA	510,385	9	142	-0.126	-0.057	0.125	0.012	0.030	0.048	-0.756	0.076	-0.138	0.002	56
	Monmouth-Ocean, NJ PMSA	1,217,783	2	124	-0.166	-0.022	0.341	0.162	0.170	2.130	0.492	0.303	-0.249	0.112	57
	Grand Junction, CO MSA	146,093	8	21	-0.171	-0.013	-0.121	-0.092	-0.085	0.382	0.629	-0.094	0.007	-0.073	58
	Minneapolis-St. Paul, MN-WI MSA	3,269,814	4	846	-0.178	-0.023	-0.038	0.017	0.115	-0.068	-0.520	0.125	0.083	-0.013	59
	Raleigh-Durham-Chapel Hill, NC MSA	1,589,388	5	782	-0.194	-0.075	-0.212	-0.056	-0.141	0.443	-1.051	-0.234	0.050	-0.028	60
	Salem, OR PMSA	396,103	9	54	-0.201	-0.205	-0.138	-0.049	0.022	0.295	0.141	0.000	0.104	-0.056	61
	Nashville, TN MSA	1,495,419	6	455	-0.220	-0.245	-0.284	-0.081	-0.149	-0.968	-0.825	-0.122	0.110	-0.050	62
	Atlantic-Cape May, NJ PMSA	367,803	2	37	-0.235	-0.346	0.134	0.070	0.148	0.736	1.675	0.098	-0.074	0.028	63
	Fort Pierce-Port St. Lucie, FL MSA	406,296	5	71	-0.236	-0.045	-0.021	-0.063	-0.106	0.358	1.663	-0.122	-0.043	64	
	Boulder-Longmont, CO PMSA	311,786	8	183	-0.238	-0.089	0.118	-0.012	-0.011	3.709	0.623	-0.092	-0.186	-0.015	65
	Danbury, CT PMSA	223,095	1	23	-0.241	-0.284	0.488	0.162	0.170	-0.605	0.492	0.303	-0.411	0.111	66
	Norfolk-Virginia Beach-Newport News, VA- MSA	1,667,410	5	392	-0.262	-0.134	-0.037	-0.071	-0.100	-0.150	1.417	-0.120	-0.107	-0.052	67
	Fresno, CA MSA	1,063,899	9	137	-0.280	-0.209	0.008	-0.017	0.128	1.078	-0.823	0.078	0.028	-0.050	68
	Worcester, MA-CT PMSA	547,274	1	56	-0.320	-0.431	0.123	0.106	0.166	3.123	0.181	0.107	-0.065	0.056	69
	Springfield, MO MSA	383,637	4	43	-0.338	-0.822	-0.540	-0.219	-0.144	-1.506	-1.122	-0.101	0.346	-0.183	70
	Savannah, GA MSA	343,092	5	64	-0.344	-0.236	-0.197	-0.097	0.165	-1.153	1.433	-0.182	0.250	-0.134	71
	Milwaukee-Waukesha, WI PMSA	1,559,667	3	399	-0.347	-0.463	-0.103	-0.030	0.110	0.375	0.558	0.048	0.111	-0.060	72
	Lakeland-Winter Haven, FL MSA	583,403	5	561	-0.350	-0.144	-0.222	-0.128	-0.147	-0.061	0.099	-0.073	0.023	-0.098	73
	Eugene-Springfield, OR MSA	351,109	9	36	-0.363	-0.300	-0.068	-0.152	-0.118	0.198	1.548	-0.004	-0.111	-0.127	74
	Tucson, AZ MSA	1,020,200	8	1,749	-0.366	-0.268	-0.095	-0.129	-0.242	2.027	-0.336	-0.138	-0.183	-0.079	75
	Myrtle Beach, SC MSA	263,868	5	84	-0.377	-0.599	-0.215	-0.243	-0.247	-1.630	1.516	-0.069	-0.186	76	
	Reading, PA MSA	407,125	2	36	-0.378	0.092	-0.314	-0.065	0.114	0.522	-0.651	0.012	0.319	-0.094	77
	Springfield, MA MSA	609,993	1	28	-0.379	-0.430	-0.056	-0.035	0.048	0.724	-0.144	0.048	0.008	-0.053	78
	Brockton, MA PMSA	268,092	1	22	-0.403	-0.307	0.266	0.106	0.166	3.116	0.181	0.117	-0.224	0.054	79
	Detroit, MI PMSA	4,373,040	3	679	-0.403	-0.378	-0.218	-0.028	0.003	-0.264	-0.267	0.049	0.129	-0.037	80
	Columbus, OH MSA	1,718,303	3	671	-0.404	-0.305	-0.307	-0.077	-0.140	0.068	-1.319	-0.049	0.103	-0.053	81
	Cincinnati, OH-KY-IN PMSA	1,776,911	3	637	-0.423	-0.387	-0.307	-0.061	-0.104	-1.281	-0.946	-0.077	0.128	-0.046	82
	Houston, TX PMSA	5,219,317	7	1,143	-0.426	-0.366	-0.366	0.023	-0.101	-0.936	-1.037	-0.124	0.189	0.032	83
	Manchester, NH PMSA	212,326	1	23	-0.426	-0.644	0.050	0.106	0.166	1.901	0.181	-0.040	-0.012	0.054	84
	Dallas, TX PMSA	4,399,895	7	811	-0.427	-0.402	-0.286	-0.008	-0.127	-0.699	-1.001	-0.144	0.087	0.008	85
	Lincoln, NE MSA	281,531	4	24	-0.432	-0.429	-0.467	-0.218	-0.308	0.849	-1.362	-0.119	0.123	-0.151	86
	Colorado Springs, CO MSA	604,542	8	892	-0.433	-0.355	-0.222	-0.134	-0.058	1.015	-0.374	-0.073	0.078	-0.124	87
	Charleston-North Charleston, SC MSA	659,191	5	214	-0.436	-0.399	-0.089	-0.131	-0.088	-1.592	1.449	-0.192	-0.080	-0.115	88
	Albuquerque, NM MSA	841,428	8	114	-0.436	-0.114	-0.238	-0.094	-0.081	0.245	-0.883	-0.102	0.075	-0.082	89
	Hamilton-Middletown, OH PMSA	363,184	3	151	-0.437	-0.209	-0.370	-0.061	-0.104	-0.300	-1.105	-0.092	0.188	-0.046	90
	Fort Collins-Loveland, CO MSA	298,382	8	344	-0.462	-0.287	-0.141	-0.101	-0.150	0.947	0.055	-0.089	-0.083	-0.075	91
	Newburgh, NY-PA PMSA	444,061	2	54	-0.475	-0.164	0.192	0.162	0.170	-0.408	-0.007	0.159	-0.160	0.105	92
	Cleveland-Lorain-Elyria, OH PMSA	2,192,053	3	416	-0.484	-0.334	-0.331	-0.097	-0.009	-0.580	0.496	0.007	0.217	-0.101	93
	Gary, IN PMSA	657,809	3	111	-0.507	-0.527	-0.356	0.055	0.203	-1.418	0.068	0.031	0.409	-0.004	94
	McAllen-Edinburg-Mission, TX MSA	741,152	7	61	-0.512	-0.494	-0.792	-0.233	-0.370	-1.035	-1.394	-0.264	0.382	-0.153	95
	Kenosha, WI PMSA	165,382	3	58	-0.519	-0.050	-0.156	0.055	0.203	0.990	0.850	0.008	0.207	-0.004	96
	Chattanooga, TN-GA MSA	510,388	6	51	-0.521	-0.531	-0.439	-0.144	-0.227	-1.459	-0.205	-0.151	0.142	-0.100	97
	Bridgeport, CT PMSA	470,094	1	26	-0.528	-0.318	0.415	0.162	0.170	0.408	0.492	0.103	-0.393	0.103	98
	Ann Arbor, MI PMSA	630,518	3	136	-0.547	-0.793	-0.100	-0.028	0.003	0.221	-0.975	0.016	-0.017	-0.040	99
	Indianapolis, IN MSA	1,823,690	3	193	-0.553	-0.513	-0.429	-0.072	-0.115	-1.401	-1.369	-0.062	0.216	-0.057	100
	Boise City, ID MSA	571,271	8	106	-0.562	-0.575	-0.261	-0.190	-0.185	-1.057	0.298	-0.115	-0.010	-0.153	101
	Champaign-Urbana, IL MSA	195,671	3	22	-0.564	-0.541	-0.387	-0.151	0.081	-0.946	-1.369	0.042	0.330	-0.173	102
	New Orleans, LA MSA	1,211,035	7	66	-0.602	-0.442	-0.203	-0.060	0.009	-2.266	2.139	-0.114	0.081	-0.073	103
	Richmond-Petersburg, VA MSA	1,119,459	5	399	-0.606	-0.428	-0.161	-0.020	-0.084	-0.925	-1.017	-0.126	-0.038	-0.017	104
	Gainesville, FL MSA	243,574	5	34	-0.611	-0.795	-0.145	-0.159	-0.055	-0.225	-0.702	-0.132	-0.030	-0.153	105
	Huntsville, AL MSA	406,316	6	29	-0.637	-0.220	-0.457	-0.057	-0.177	-2.298	-0.276	-0.151	0.177	-0.033	106
	Pittsburgh, PA MSA	2,287,106	2	240	-0.646	-0.821	-0.445	-0.100	-0.105	-0.183	-0.004	0.013	0.221	-0.087	107
	St. Louis, MO-IL MSA	2,733,694	4	364	-0.654	-0.641	-0.304	-0.055	0.143	-1.361	-0.909	0.040	0.282	-0.098	108

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

	Full Name	Population	Cen- sus Div- ision	Obs. Land Sales	Adjusted Differentials				Raw Differentials			Productivity			
					Land Value (No Wts.)	Housing Cost	Wages (All)	Wages (Const. Only)	Geo Avail. Index (z-score)	Const. Cost Index	Tradea- bles	Land Value Rank			
	Asheville, NC MSA	251,894	5	41	-0.668	-0.453	-0.166	-0.218	-0.368	-1.288	1.785	-0.267	-0.273	-0.144	109
	Merced, CA MSA	245,321	9	64	-0.686	-0.176	-0.022	-0.044	-0.116	0.657	-0.953	-0.217	-0.034	-0.110	110
	Daytona Beach, FL MSA	587,512	5	93	-0.707	-0.126	-0.109	-0.152	-0.039	0.409	1.453	-0.110	-0.072	-0.152	111
	Rockford, IL MSA	409,058	3	104	-0.720	-0.621	-0.469	-0.092	0.070	-1.162	-1.334	0.100	0.375	-0.119	112
	York, PA MSA	428,937	2	47	-0.742	-0.479	-0.300	-0.050	0.003	1.020	-0.860	-0.024	0.147	-0.066	113
	Biloxi-Gulfport-Pascagoula, MS MSA	355,075	6	30	-0.744	-0.968	-0.385	-0.132	-0.123	-1.880	1.049	-0.181	0.129	-0.116	114
	Brazoria, TX PMSA	309,208	7	62	-0.751	-0.916	-0.434	0.023	-0.101	-1.144	-1.037	-0.124	0.195	0.024	115
	La Crosse, WI-MN MSA	132,923	3	21	-0.758	-0.507	-0.431	-0.121	0.154	0.307	0.271	-0.054	0.399	-0.164	116
	Harrisburg-Lebanon-Carlisle, PA MSA	667,425	2	89	-0.767	-0.542	-0.332	-0.084	0.053	0.456	-0.291	-0.014	0.216	-0.109	117
	Akron, OH PMSA	699,935	3	169	-0.771	-0.555	-0.360	-0.097	-0.009	-0.231	-1.130	-0.027	0.192	-0.108	118
	Fayetteville-Springdale-Rogers, AR MSA	425,685	7	43	-0.775	-0.474	-0.338	-0.102	-0.179	-0.966	-0.056	-0.275	0.031	-0.077	119
	Greeley, CO PMSA	254,759	8	320	-0.775	-0.434	-0.276	-0.012	-0.011	-0.433	-0.957	-0.157	0.106	-0.028	120
	Lexington, KY MSA	554,107	6	29	-0.780	-0.445	-0.364	-0.123	-0.165	-0.045	-1.156	-0.123	0.066	-0.100	121
	Fort Worth-Arlington, TX PMSA	2,113,278	7	506	-0.791	-0.608	-0.377	-0.008	-0.127	-0.736	-1.204	-0.175	0.109	-0.001	122
	Greensboro--Winston Salem--High Point, NC MSA	1,416,374	5	438	-0.803	-0.598	-0.411	-0.139	-0.206	-0.919	-1.289	-0.244	0.076	-0.107	123
	Hartford, CT MSA	1,231,125	1	101	-0.806	-0.772	0.098	0.089	0.120	0.405	-0.326	0.100	-0.167	0.038	124
	Omaha, NE-IA MSA	799,130	4	118	-0.813	-0.702	-0.437	-0.107	-0.086	-1.206	-1.279	-0.095	0.199	-0.103	125
	Tulsa, OK MSA	873,304	7	245	-0.816	-0.669	-0.453	-0.117	-0.098	-1.497	-1.138	-0.222	0.204	-0.109	126
	Little Rock-North Little Rock, AR MSA	657,416	7	110	-0.817	-0.963	-0.404	-0.140	-0.191	-1.658	-0.784	-0.159	0.079	-0.111	127
	Dutchess County, NY PMSA	293,562	2	33	-0.838	-0.453	0.230	0.162	0.170	0.217	0.492	0.159	-0.263	0.096	128
	Richland-Kennewick-Pasco, WA MSA	245,649	9	27	-0.869	-0.569	-0.410	0.033	0.119	0.892	-0.852	-0.040	0.330	-0.016	129
	Lancaster, PA MSA	507,766	2	57	-0.869	-0.490	-0.241	-0.084	0.018	0.114	-0.870	-0.065	0.077	-0.105	130
	Columbia, SC MSA	627,630	5	139	-0.870	-1.046	-0.367	-0.124	-0.151	-1.527	-0.711	-0.238	0.065	-0.106	131
	Canton-Massillon, OH MSA	408,005	3	40	-0.876	-0.853	-0.510	-0.136	-0.099	-1.593	-0.837	-0.069	0.250	-0.129	132
	Billings, MT MSA	144,797	8	25	-0.892	-0.562	-0.401	-0.182	0.046	-0.638	-0.896	-0.098	0.256	-0.203	133
	Racine, WI PMSA	200,601	3	80	-0.897	-0.745	-0.214	-0.030	0.110	-0.667	1.146	0.012	0.121	-0.074	134
	Spokane, WA MSA	468,684	9	55	-0.901	-0.767	-0.286	-0.142	0.099	0.734	-0.133	-0.056	0.183	-0.176	135
	Louisville, KY-IN MSA	1,099,588	6	126	-0.908	-0.702	-0.409	-0.114	-0.052	-1.061	-0.832	-0.082	0.181	-0.118	136
	Memphis, TN-AR-MS MSA	1,230,253	6	173	-0.939	-0.717	-0.387	-0.066	-0.134	1.503	-0.856	-0.140	0.086	-0.057	137
	Baton Rouge, LA MSA	685,419	7	99	-0.956	-0.696	-0.305	-0.068	-0.026	-1.603	0.163	-0.152	0.090	-0.082	138
	San Antonio, TX MSA	1,928,154	7	348	-0.996	-0.867	-0.510	-0.127	-0.201	-0.668	-1.287	-0.190	0.144	-0.101	139
	Knoxville, TN MSA	785,490	6	193	-1.004	-0.838	-0.408	-0.158	-0.322	-0.916	0.402	-0.204	-0.059	-0.106	140
	Johnson City-Kingsport-Bristol, TN-VA MSA	503,010	6	28	-1.008	-0.797	-0.571	-0.212	-0.427	-1.701	1.203	-0.224	0.018	-0.134	141
	Roanoke, VA MSA	243,506	5	23	-1.009	-0.824	-0.390	-0.120	-0.260	-1.199	0.446	-0.163	-0.028	-0.083	142
	Dayton-Springfield, OH MSA	933,312	3	116	-1.010	-0.780	-0.449	-0.129	-0.211	-1.052	-1.388	-0.094	0.072	-0.102	143
	Kansas City, MO-KS MSA	2,005,888	4	477	-1.042	-0.705	-0.359	-0.062	0.036	-1.571	-1.160	0.045	0.181	-0.091	144
	Amarillo, TX MSA	238,299	7	27	-1.046	-1.011	-0.520	-0.211	-0.317	-0.957	-1.271	-0.184	0.050	-0.157	145
	Galveston-Texas City, TX PMSA	286,814	7	39	-1.050	-0.713	-0.366	0.023	-0.101	0.684	2.149	-0.142	0.072	0.017	146
	Bakersfield, CA MSA	807,407	9	64	-1.057	-0.780	-0.048	0.038	0.085	0.279	-0.282	0.062	-0.093	-0.008	147
	El Paso, TX MSA	751,296	7	94	-1.060	-0.811	-0.666	-0.241	-0.478	0.797	-1.193	-0.237	0.062	-0.152	148
	Greenville-Spartanburg-Anderson, SC MSA	1,096,009	5	507	-1.061	-0.960	-0.467	-0.135	-0.260	-1.793	-0.824	-0.255	0.040	-0.099	149
	Syracuse, NY MSA	725,610	2	65	-1.065	-1.557	-0.509	-0.083	0.003	-1.249	-0.586	-0.019	0.298	-0.105	150
	Hickory-Morganton-Lenoir, NC MSA	365,364	5	88	-1.069	-0.835	-0.495	-0.225	-0.151	-1.234	-0.437	-0.306	0.157	-0.205	151
	Augusta-Aiken, GA-SC MSA	516,357	5	66	-1.074	-1.086	-0.476	-0.113	-0.205	-2.037	-0.940	-0.170	0.093	-0.090	152
	Bryan-College Station, TX MSA	179,992	7	34	-1.090	-1.319	-0.393	-0.195	-0.180	0.262	-1.132	-0.199	0.028	-0.172	153
	Oklahoma City, OK MSA	1,213,704	7	395	-1.122	-0.909	-0.431	-0.143	-0.115	-0.867	-1.321	-0.178	0.114	-0.138	154
	Green Bay, WI MSA	247,319	3	49	-1.146	-0.744	-0.333	-0.099	-0.069	0.557	-0.326	-0.033	0.049	-0.107	155
	Brownsville-Harlingen-San Benito, TX MSA	396,371	7	52	-1.157	-1.069	-0.783	-0.227	-0.372	-1.825	-0.119		0.248	-0.163	156
	Jackson, MS MSA	483,852	6	43	-1.185	-1.092	-0.417	-0.139	-0.248	-1.473	-0.897	-0.155	-0.021	-0.108	157
	Des Moines, IA MSA	536,664	4	99	-1.185	-0.959	-0.381	-0.053	-0.089	-1.645	-1.143	-0.115	0.074	-0.061	158
	Montgomery, AL MSA	354,108	6	33	-1.197	-1.276	-0.437	-0.144	-0.340	-1.881	-0.924	-0.207	-0.079	-0.093	159
	Scranton--Wilkes-Barre--Hazleton, PA MSA	614,565	2	27	-1.227	-1.101	-0.456	-0.132	-0.046	-0.324	-0.063	0.015	0.178	-0.145	160
	Rochester, NY MSA	1,093,434	2	110	-1.279	-2.028	-0.482	-0.092	-0.058	-0.425	0.017	0.003	0.185	-0.106	161
	Wichita, KS MSA	589,195	4	54	-1.290	-1.078	-0.590	-0.086	-0.043	-2.185	-1.359	-0.179	0.304	-0.103	162
	Davenport-Moline-Rock Island, IA-IL MSA	362,790	4	28	-1.313	-1.192	-0.500	-0.130	0.015	-1.758	-1.220	-0.054	0.259	-0.157	163

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

Full Name	Population	Cen- sus Div- ision	Obs. Land Sales	Adjusted Differentials				Raw Differentials			Productivity			Land Value Rank
				Land Value (No Wts.)	Housing Cost	Wages (All)	Wages (Const. Only)	Reg. Index (z-score)	Geo Avail. Index (z-score)	Const. Cost Index	Housing	Tradea- bles		
Pensacola, FL MSA	455,102	5	102	-1.316	-1.095	-0.335	-0.179	-0.224	-1.671	1.073	-0.140	-0.107	-0.154	164
Buffalo-Niagara Falls, NY MSA	1,123,804	2	104	-1.317	-1.163	-0.487	-0.079	-0.017	-0.652	-0.528	0.030	0.218	-0.104	165
Kalamazoo-Battle Creek, MI MSA	462,250	3	31	-1.320	-1.318	-0.469	-0.159	-0.242	-0.207	-0.967	-0.065	0.012	-0.131	166
Grand Rapids-Muskegon-Holland, MI MSA	1,157,672	3	121	-1.336	-1.270	-0.425	-0.131	-0.124	-0.553	-0.995	-0.125	0.064	-0.130	167
Flint, MI PMSA	424,043	3	85	-1.354	-1.152	-0.605	-0.028	0.003	-0.828	-0.981	-0.013	0.347	-0.060	168
Lansing-East Lansing, MI MSA	453,603	3	40	-1.358	-1.335	-0.383	-0.128	-0.015	-0.036	-1.111	-0.014	0.109	-0.151	169
Corpus Christi, TX MSA	391,269	7	74	-1.359	-1.260	-0.412	-0.177	-0.090	-0.719	0.378	-0.233	0.075	-0.181	170
Cedar Rapids, IA MSA	209,226	4	33	-1.370	-1.098	-0.471	-0.088	-0.213	-0.978	-1.269	-0.091	0.029	-0.072	171
Fort Wayne, IN MSA	528,408	3	39	-1.377	-1.078	-0.614	-0.153	-0.129	-2.236	-1.316	-0.108	0.242	-0.151	172
Birmingham, AL MSA	997,770	6	148	-1.383	-1.003	-0.298	-0.068	-0.114	-0.702	-0.753	-0.116	-0.063	-0.074	173
Beaumont-Port Arthur, TX MSA	378,477	7	60	-1.387	-1.365	-0.589	-0.042	0.004	-1.329	-0.538	-0.179	0.327	-0.075	174
Mobile, AL MSA	591,599	6	135	-1.420	-1.275	-0.397	-0.142	-0.184	-1.891	-0.038	-0.158	-0.029	-0.130	175
Fayetteville, NC MSA	315,207	5	25	-1.428	-1.160	-0.496	-0.177	-0.257	-1.128	-0.697	-0.232	0.008	-0.148	176
Albany-Schenectady-Troy, NY MSA	906,208	2	120	-1.429	-1.463	-0.188	-0.032	-0.048	-0.459	-0.324	-0.007	-0.125	-0.055	177
Lubbock, TX MSA	270,550	7	45	-1.477	-1.298	-0.480	-0.183	-0.234	-1.842	-1.416	-0.212	0.003	-0.159	178
Toledo, OH MSA	631,275	3	107	-1.553	-1.418	-0.430	-0.123	0.056	-1.219	-0.532	-0.013	0.185	-0.165	179
Killeen-Temple, TX MSA	358,316	7	32	-1.559	-1.420	-0.491	-0.158	-0.284	-1.908	-1.279	-0.263	-0.041	-0.127	180
Duluth-Superior, MN-WI MSA	242,041	4	22	-1.607	-1.381	-0.385	-0.098	-0.027	-0.908	0.206	0.071	0.062	-0.127	181
Appleton-Oshkosh-Neenah, WI MSA	385,264	3	79	-1.623	-1.379	-0.399	-0.095	-0.049	-0.607	-0.581	-0.071	0.055	-0.119	182
Erie, PA MSA	280,291	2	29	-1.678	-1.609	-0.595	-0.174	-0.008	-1.312	0.997	-0.045	0.277	-0.203	183
Peoria-Pekin, IL MSA	357,144	3	25	-1.808	-1.663	-0.501	-0.065	0.112	-0.924	-1.200	0.041	0.267	-0.129	184
Macon, GA MSA	356,873	5	20	-1.819	-1.283	-0.498	-0.149	-0.266	-1.643	-1.061	-0.175	-0.059	-0.129	185
Youngstown-Warren, OH MSA	554,614	3	49	-1.850	-1.686	-0.593	-0.170	-0.092	-0.932	-0.936	-0.042	0.179	-0.186	186
Glens Falls, NY MSA	128,774	2	21	-1.915	-1.965	-0.315	-0.102	-0.152	-2.836	0.514	-0.072	-0.161	-0.112	187
Evansville-Henderson, IN-KY MSA	305,455	3	33	-2.083	-1.905	-0.482	-0.123	-0.019	-1.965	-1.024	-0.073	0.098	-0.163	188
Saginaw-Bay City-Midland, MI MSA	390,032	3	41	-2.087	-1.964	-0.512	-0.134	-0.059	-0.354	-0.655	-0.038	0.092	-0.165	189
<i>Census Divisions:</i>														
New England	8,342,917	1	498	0.051	-0.069	0.283	0.095	0.138	1.550	0.167	0.127	-0.169	0.061	4
Middle Atlantic	35,800,794	2	4,536	0.472	0.291	0.164	0.080	0.112	0.582	0.029	0.165	0.035	0.063	2
East North Central	33,339,322	3	8,452	-0.373	-0.430	-0.220	-0.041	0.028	-0.515	-0.335	0.029	0.165	-0.054	6
West North Central	11,413,610	4	2,108	-0.693	-0.559	-0.288	-0.054	0.045	-1.019	-0.913	0.024	0.181	-0.078	8
South Atlantic	41,354,210	5	19,462	0.047	0.103	-0.022	-0.035	-0.107	-0.020	0.119	-0.107	-0.057	-0.009	5
East South Central	9,366,975	6	1,473	-0.877	-0.722	-0.384	-0.111	-0.181	-0.845	-0.459	-0.144	0.058	-0.088	9
West South Central	24,734,026	7	4,730	-0.679	-0.609	-0.389	-0.059	-0.142	-0.931	-0.829	-0.168	0.131	-0.043	7
Mountain	15,672,803	8	14,517	0.068	0.145	-0.062	-0.039	-0.016	0.313	-0.098	-0.099	0.055	-0.031	3
Pacific	39,829,108	9	10,785	0.651	0.662	0.428	0.081	0.098	0.537	0.901	0.088	-0.214	0.071	1
<i>Population Categories:</i>														
Less than 500,000	25,078,538		4,642	-0.741	-0.657	-0.219	-0.067	-0.045	-0.272	-0.061	-0.059	0.033	-0.071	4
500,000 to 1,500,000	55,777,644		13,942	-0.573	-0.477	-0.193	-0.058	-0.059	-0.259	-0.207	-0.063	0.027	-0.056	3
1,500,000 to 5,000,000	89,173,333		32,032	0.150	0.162	0.058	0.012	0.014	0.116	0.117	0.002	-0.020	0.012	2
5,000,000+	49,824,250		15,945	0.765	0.579	0.212	0.082	0.076	0.209	-0.041	0.100	0.012	0.080	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	Residential Land Sales	Land Diff. 1	Land Diff. 2	Land Diff. 3	Land Diff. 4	Land Diff. 5
New York, NY PMSA	1,603	443	3.365	1.663	1.529	1.922	1.512
San Francisco, CA PMSA	152	54	2.541	1.568	1.447	1.820	1.747
Jersey City, NJ PMSA	43	10	2.428	1.433	1.487	1.450	1.273
San Jose, CA PMSA	217	68	1.723	1.393	1.247	1.256	1.215
Orange County, CA PMSA	233	46	1.899	1.277	1.204	1.092	1.096
San Diego, CA MSA	957	216	0.907	0.956	0.862	1.087	1.082
Miami, FL PMSA	1,233	143	1.405	1.019	0.926	0.980	0.709
Seattle-Bellevue-Everett, WA PMSA	1,626	682	1.210	0.935	0.828	0.951	0.766
Los Angeles-Long Beach, CA PMSA	1,760	476	1.696	1.084	0.972	0.937	0.731
Oakland, CA PMSA	132	32	1.593	1.081	0.848	0.912	0.582
Las Vegas, NV-AZ MSA	2,553	369	0.753	0.958	0.856	0.849	0.689
West Palm Beach-Boca Raton, FL MSA	321	40	1.432	1.001	0.776	0.828	0.772
Fort Lauderdale, FL PMSA	741	96	1.390	1.018	0.871	0.805	0.532
Newark, NJ PMSA	142	16	0.661	0.235	0.364	0.712	0.648
Washington, DC-MD-VA-WV PMSA	1,840	270	0.612	0.728	0.674	0.677	0.779
Santa Barbara-Santa Maria-Lompoc, CA MSA	29	1	1.379	0.538	0.707	0.665	0.416
Chicago, IL PMSA	3,511	522	0.003	0.338	0.262	0.664	0.750
Philadelphia, PA-NJ PMSA	859	159	-0.185	0.161	0.132	0.607	0.492
Ventura, CA PMSA	131	31	0.476	0.751	0.717	0.605	0.483
Nassau-Suffolk, NY PMSA	396	44	0.824	0.675	0.674	0.583	0.575
Bergen-Passaic, NJ PMSA	79	7	1.226	0.674	0.717	0.577	-0.045
Boston, MA-NH PMSA	122	19	0.385	0.386	0.482	0.566	0.007
Portland, ME MSA	25	1	-0.708	-1.059	-0.962	0.540	1.243
Naples, FL MSA	78	12	0.327	0.521	0.503	0.519	-0.074
Vallejo-Fairfield-Napa, CA PMSA	146	13	0.298	0.487	0.400	0.365	0.078
Orlando, FL MSA	1,612	159	0.035	0.448	0.388	0.331	0.124
Sarasota-Bradenton, FL MSA	601	50	0.089	0.455	0.382	0.325	0.064
Madison, WI MSA	239	51	-0.462	-0.242	-0.328	0.305	-0.314
Tacoma, WA PMSA	539	177	0.191	0.440	0.386	0.295	0.269
Portland-Vancouver, OR-WA PMSA	1,191	349	0.339	0.414	0.372	0.294	0.373
Tampa-St. Petersburg-Clearwater, FL MSA	1,220	146	0.286	0.393	0.316	0.275	0.082
Hagerstown, MD PMSA	28	4	-1.443	-0.504	-0.477	0.259	0.179
San Luis Obispo-Atascadero-Paso Robles, CA MSA	43	13	1.065	0.280	0.285	0.241	-0.060
Middlesex-Somerset-Hunterdon, NJ PMSA	101	14	-0.026	0.201	0.402	0.238	-0.283
Phoenix-Mesa, AZ MSA	5,946	1,476	-0.530	0.400	0.358	0.216	-0.009
New Haven-Meriden, CT PMSA	43	5	-0.010	-0.248	-0.152	0.210	-0.638
Baltimore, MD PMSA	802	126	0.192	0.238	0.198	0.207	0.304
Santa Rosa, CA PMSA	153	36	0.260	0.598	0.534	0.197	0.071
Melbourne-Titusville-Palm Bay, FL MSA	420	31	-0.255	0.224	0.142	0.154	-0.426
Lawrence, MA-NH PMSA	29	3	-0.329	-0.296	-0.178	0.136	-0.785
Reno, NV MSA	57	15	-0.203	-0.072	0.096	0.119	-0.586
Provo-Orem, UT MSA	47	6	0.204	0.076	0.168	0.108	-0.063
Olympia, WA PMSA	250	100	-0.291	0.141	0.067	0.107	0.006
Denver, CO PMSA	2,015	557	0.103	0.054	-0.060	0.076	-0.037
Riverside-San Bernardino, CA PMSA	2,452	438	-0.395	0.156	0.102	-0.007	-0.341
Stockton-Lodi, CA MSA	163	17	-0.090	0.059	0.115	-0.039	-0.298
Wilmington-Newark, DE-MD PMSA	107	8	-0.541	-0.008	0.008	-0.059	-1.294
Jacksonville, FL MSA	793	100	-0.277	0.161	0.132	-0.062	-0.168
Salt Lake City-Ogden, UT MSA	145	10	0.205	-0.090	0.077	-0.062	-0.383
Austin-San Marcos, TX MSA	384	39	-0.708	-0.312	-0.382	-0.081	-0.532
Visalia-Tulare-Porterville, CA MSA	32	4	-0.131	-0.489	-0.271	-0.088	-0.843

TABLE A3: DIFFERENT MEASURES OF THE LAND PRICE DIFFERENTIAL

Full Name	Total Land Sales	Residential Land Sales	Land Diff. 1	Land Diff. 2	Land Diff. 3	Land Diff. 4	Land Diff. 5
Allentown-Bethlehem-Easton, PA MSA	85	7	-0.681	-0.107	0.038	-0.088	-0.544
Atlanta, GA MSA	5,229	488	-0.586	-0.007	-0.100	-0.090	-0.335
Trenton, NJ PMSA	35	0	-0.312	0.120	0.254	-0.091	
Fort Myers-Cape Coral, FL MSA	294	44	-0.080	-0.014	0.098	-0.092	-0.266
Modesto, CA MSA	142	13	-0.158	-0.039	-0.057	-0.126	-0.248
Monmouth-Ocean, NJ PMSA	124	11	-0.320	-0.214	-0.022	-0.166	0.360
Grand Junction, CO MSA	21	1	-0.394	-0.158	-0.013	-0.171	-0.172
Minneapolis-St. Paul, MN-WI MSA	846	139	-0.045	0.042	-0.023	-0.178	-0.488
Raleigh-Durham-Chapel Hill, NC MSA	782	139	-0.479	-0.126	-0.075	-0.194	-0.411
Salem, OR PMSA	54	7	-0.191	-0.367	-0.205	-0.201	-0.361
Nashville, TN MSA	455	44	-0.355	-0.330	-0.245	-0.220	-0.314
Atlantic-Cape May, NJ PMSA	37	4	-0.367	-0.500	-0.346	-0.235	-0.237
Fort Pierce-Port St. Lucie, FL MSA	71	8	-0.302	-0.159	-0.045	-0.236	-0.823
Boulder-Longmont, CO PMSA	183	33	-0.114	0.017	-0.089	-0.238	-0.116
Danbury, CT PMSA	23	3	-0.478	-0.370	-0.284	-0.241	-0.935
Norfolk-Virginia Beach-Newport News, VA- MSA	392	63	-0.536	-0.182	-0.134	-0.262	-0.167
Fresno, CA MSA	137	33	-0.979	-0.356	-0.209	-0.280	-0.094
Worcester, MA-CT PMSA	56	7	-0.768	-0.509	-0.431	-0.320	-1.383
Springfield, MO MSA	43	4	-0.860	-0.937	-0.822	-0.338	-1.574
Savannah, GA MSA	64	6	-0.856	-0.451	-0.236	-0.344	-0.025
Milwaukee-Waukesha, WI PMSA	399	46	-0.776	-0.466	-0.463	-0.347	-0.777
Lakeland-Winter Haven, FL MSA	561	73	-0.919	-0.074	-0.144	-0.350	-0.839
Eugene-Springfield, OR MSA	36	7	-0.405	-0.526	-0.300	-0.363	-0.014
Tucson, AZ MSA	1,749	793	-0.481	-0.217	-0.268	-0.366	-0.484
Myrtle Beach, SC MSA	84	15	-0.431	-0.582	-0.599	-0.377	-0.723
Reading, PA MSA	36	1	-0.462	-0.039	0.092	-0.378	-0.593
Springfield, MA MSA	28	2	-0.459	-0.646	-0.430	-0.379	0.183
Brockton, MA PMSA	22	4	-1.001	-0.289	-0.307	-0.403	-0.381
Detroit, MI PMSA	679	99	-0.543	-0.386	-0.378	-0.403	-0.844
Columbus, OH MSA	671	89	-0.716	-0.282	-0.305	-0.404	-0.673
Cincinnati, OH-KY-IN PMSA	637	68	-0.696	-0.351	-0.387	-0.423	-0.963
Houston, TX PMSA	1,143	94	-0.523	-0.342	-0.366	-0.426	-0.421
Manchester, NH PMSA	23	3	-0.765	-0.757	-0.644	-0.426	-0.409
Dallas, TX PMSA	811	74	-0.423	-0.362	-0.402	-0.427	-0.362
Lincoln, NE MSA	24	1	-0.768	-0.714	-0.429	-0.432	-0.702
Colorado Springs, CO MSA	892	409	-0.162	-0.213	-0.355	-0.433	-0.591
Charleston-North Charleston, SC MSA	214	24	-0.473	-0.466	-0.399	-0.436	-0.426
Albuquerque, NM MSA	114	6	0.072	-0.193	-0.114	-0.436	-0.673
Hamilton-Middletown, OH PMSA	151	13	-0.705	-0.175	-0.209	-0.437	-1.515
Fort Collins-Loveland, CO MSA	344	68	-0.276	-0.167	-0.287	-0.462	-0.506
Newburgh, NY-PA PMSA	54	7	-1.005	-0.373	-0.164	-0.475	-0.308
Cleveland-Lorain-Elyria, OH PMSA	416	36	-0.637	-0.345	-0.334	-0.484	-0.932
Gary, IN PMSA	111	9	-0.647	-0.565	-0.527	-0.507	-1.556
McAllen-Edinburg-Mission, TX MSA	61	4	-0.667	-0.660	-0.494	-0.512	-0.743
Kenosha, WI PMSA	58	6	-1.017	-0.080	-0.050	-0.519	-1.182
Chattanooga, TN-GA MSA	51	2	-0.536	-0.608	-0.531	-0.521	-1.276
Bridgeport, CT PMSA	26	2	0.351	-0.433	-0.318	-0.528	0.430
Ann Arbor, MI PMSA	136	17	-1.381	-0.815	-0.793	-0.547	-0.961
Indianapolis, IN MSA	193	16	-0.893	-0.645	-0.513	-0.553	-0.658
Boise City, ID MSA	106	15	-0.465	-0.649	-0.575	-0.562	-0.660
Champaign-Urbana, IL MSA	22	4	-0.635	-0.663	-0.541	-0.564	-0.486

TABLE A3: DIFFERENT MEASURES OF THE LAND PRICE DIFFERENTIAL

Full Name	Total Land Sales	Residential Land Sales	Land Diff. 1	Land Diff. 2	Land Diff. 3	Land Diff. 4	Land Diff. 5
New Orleans, LA MSA	66	8	-0.211	-0.577	-0.442	-0.602	-0.796
Richmond-Petersburg, VA MSA	399	73	-0.819	-0.427	-0.428	-0.606	-0.661
Gainesville, FL MSA	34	4	-0.895	-0.928	-0.795	-0.611	-1.395
Huntsville, AL MSA	29	1	-0.734	-0.353	-0.220	-0.637	-1.307
Pittsburgh, PA MSA	240	20	-1.185	-0.998	-0.821	-0.646	-0.939
St. Louis, MO-IL MSA	364	45	-0.867	-0.741	-0.641	-0.654	-1.199
Asheville, NC MSA	41	8	-0.688	-0.519	-0.453	-0.668	-1.090
Merced, CA MSA	64	15	-0.728	-0.167	-0.176	-0.686	-0.438
Daytona Beach, FL MSA	93	13	-0.305	-0.188	-0.126	-0.707	-0.238
Rockford, IL MSA	104	3	-1.757	-0.757	-0.621	-0.720	-1.080
York, PA MSA	47	1	-1.093	-0.658	-0.479	-0.742	-1.695
Biloxi-Gulfport-Pascagoula, MS MSA	30	6	-1.180	-1.081	-0.968	-0.744	-1.020
Brazoria, TX PMSA	62	4	-1.286	-0.979	-0.916	-0.751	-2.356
La Crosse, WI-MN MSA	21	2	-0.265	-0.782	-0.507	-0.758	-0.839
Harrisburg-Lebanon-Carlisle, PA MSA	89	5	-0.858	-0.565	-0.542	-0.767	-1.647
Akron, OH PMSA	169	16	-1.006	-0.555	-0.555	-0.771	-1.149
Fayetteville-Springdale-Rogers, AR MSA	43	3	-0.587	-0.521	-0.474	-0.775	-1.396
Greeley, CO PMSA	320	74	-1.034	-0.319	-0.434	-0.775	-0.996
Lexington, KY MSA	29	1	-0.202	-0.539	-0.445	-0.780	-1.410
Fort Worth-Arlington, TX PMSA	506	39	-0.524	-0.576	-0.608	-0.791	-0.928
Greensboro--Winston Salem--High Point, NC MSA	438	71	-0.912	-0.659	-0.598	-0.803	-1.188
Hartford, CT MSA	101	8	-0.950	-0.873	-0.772	-0.806	-2.618
Omaha, NE-IA MSA	118	10	-0.640	-0.786	-0.702	-0.813	-1.531
Tulsa, OK MSA	245	11	-0.649	-0.736	-0.669	-0.816	-1.948
Little Rock-North Little Rock, AR MSA	110	9	-0.924	-1.082	-0.963	-0.817	-1.711
Dutchess County, NY PMSA	33	7	-1.595	-0.633	-0.453	-0.838	-0.696
Richland-Kennewick-Pasco, WA MSA	27	1	-0.325	-0.626	-0.569	-0.869	-1.346
Lancaster, PA MSA	57	5	-1.126	-0.721	-0.490	-0.869	-0.685
Columbia, SC MSA	139	15	-1.096	-1.123	-1.046	-0.870	-1.554
Canton-Massillon, OH MSA	40	1	-1.195	-1.086	-0.853	-0.876	-0.758
Billings, MT MSA	25	4	-0.582	-0.541	-0.562	-0.892	-0.821
Racine, WI PMSA	80	14	-1.378	-0.727	-0.745	-0.897	-1.622
Spokane, WA MSA	55	5	-0.338	-0.842	-0.767	-0.901	-1.445
Louisville, KY-IN MSA	126	19	-0.728	-0.805	-0.702	-0.908	-1.137
Memphis, TN-AR-MS MSA	173	19	-0.939	-0.832	-0.717	-0.939	-0.825
Baton Rouge, LA MSA	99	11	-0.678	-0.710	-0.696	-0.956	-1.764
San Antonio, TX MSA	348	30	-0.937	-0.886	-0.867	-0.996	-1.179
Knoxville, TN MSA	193	27	-0.990	-0.896	-0.838	-1.004	-1.805
Johnson City-Kingsport-Bristol, TN-VA MSA	28	2	-0.979	-0.882	-0.797	-1.008	-2.362
Roanoke, VA MSA	23	0	-0.728	-0.940	-0.824	-1.009	
Dayton-Springfield, OH MSA	116	7	-0.902	-0.850	-0.780	-1.010	-2.282
Kansas City, MO-KS MSA	477	57	-0.735	-0.632	-0.705	-1.042	-1.515
Amarillo, TX MSA	27	1	-1.087	-1.110	-1.011	-1.046	-1.967
Galveston-Texas City, TX PMSA	39	6	-0.867	-0.730	-0.713	-1.050	-1.332
Bakersfield, CA MSA	64	14	-1.157	-0.926	-0.780	-1.057	-1.996
El Paso, TX MSA	94	5	-0.547	-0.950	-0.811	-1.060	-2.039
Greenville-Spartanburg-Anderson, SC MSA	507	67	-1.194	-1.002	-0.960	-1.061	-1.512
Syracuse, NY MSA	65	6	-2.169	-1.784	-1.557	-1.065	-2.176
Hickory-Morganton-Lenoir, NC MSA	88	13	-1.492	-0.947	-0.835	-1.069	-1.401
Augusta-Aiken, GA-SC MSA	66	3	-1.115	-1.216	-1.086	-1.074	-1.200
Bryan-College Station, TX MSA	34	4	-1.584	-1.472	-1.319	-1.090	-1.895

TABLE A3: DIFFERENT MEASURES OF THE LAND PRICE DIFFERENTIAL

Full Name	Total Land Sales	Residential Land Sales	Land Diff. 1	Land Diff. 2	Land Diff. 3	Land Diff. 4	Land Diff. 5
Oklahoma City, OK MSA	395	17	-0.932	-1.019	-0.909	-1.122	-1.788
Green Bay, WI MSA	49	5	-0.840	-0.977	-0.744	-1.146	-1.219
Brownsville-Harlingen-San Benito, TX MSA	52	10	-0.996	-1.230	-1.069	-1.157	-1.346
Jackson, MS MSA	43	1	-1.299	-1.147	-1.092	-1.185	-3.145
Des Moines, IA MSA	99	9	-1.079	-1.088	-0.959	-1.185	-2.001
Montgomery, AL MSA	33	3	-1.193	-1.390	-1.276	-1.197	0.146
Scranton--Wilkes-Barre--Hazleton, PA MSA	27	2	-1.618	-1.265	-1.101	-1.227	-2.350
Rochester, NY MSA	110	12	-2.582	-2.277	-2.028	-1.279	-2.910
Wichita, KS MSA	54	2	-1.118	-1.254	-1.078	-1.290	-2.685
Davenport-Moline-Rock Island, IA-IL MSA	28	1	-1.204	-1.328	-1.192	-1.313	-0.909
Pensacola, FL MSA	102	8	-0.780	-1.237	-1.095	-1.316	-1.665
Buffalo-Niagara Falls, NY MSA	104	5	-1.188	-1.279	-1.163	-1.317	-1.432
Kalamazoo-Battle Creek, MI MSA	31	2	-1.403	-1.510	-1.318	-1.320	-2.365
Grand Rapids-Muskegon-Holland, MI MSA	121	14	-1.175	-1.400	-1.270	-1.336	-1.817
Flint, MI PMSA	85	17	-1.682	-1.227	-1.152	-1.354	-2.143
Lansing-East Lansing, MI MSA	40	4	-1.475	-1.443	-1.335	-1.358	-0.810
Corpus Christi, TX MSA	74	6	-1.134	-1.315	-1.260	-1.359	-1.561
Cedar Rapids, IA MSA	33	1	-1.050	-1.176	-1.098	-1.370	-3.373
Fort Wayne, IN MSA	39	2	-1.351	-1.094	-1.078	-1.377	-4.318
Birmingham, AL MSA	148	5	-0.924	-1.032	-1.003	-1.383	-3.237
Beaumont-Port Arthur, TX MSA	60	5	-1.402	-1.490	-1.365	-1.387	-2.843
Mobile, AL MSA	135	18	-1.421	-1.366	-1.275	-1.420	-2.021
Fayetteville, NC MSA	25	4	-0.842	-1.238	-1.160	-1.428	-1.342
Albany-Schenectady-Troy, NY MSA	120	24	-1.774	-1.597	-1.463	-1.429	-1.974
Lubbock, TX MSA	45	0	-1.529	-1.367	-1.298	-1.477	
Toledo, OH MSA	107	6	-1.519	-1.466	-1.418	-1.553	-3.294
Killeen-Temple, TX MSA	32	0	-1.330	-1.478	-1.420	-1.559	
Duluth-Superior, MN-WI MSA	22	1	-1.189	-1.372	-1.381	-1.607	-1.045
Appleton-Oshkosh-Neenah, WI MSA	79	9	-1.812	-1.547	-1.379	-1.623	-1.963
Erie, PA MSA	29	3	-1.680	-1.748	-1.609	-1.678	-1.799
Peoria-Pekin, IL MSA	25	2	-2.028	-1.829	-1.663	-1.808	-1.914
Macon, GA MSA	20	2	-1.430	-1.351	-1.283	-1.819	-0.576
Youngstown-Warren, OH MSA	49	3	-1.957	-1.832	-1.686	-1.850	-2.738
Glens Falls, NY MSA	21	3	-2.847	-2.104	-1.965	-1.915	-3.095
Evansville-Henderson, IN-KY MSA	33	0	-1.644	-1.962	-1.905	-2.083	
Saginaw-Bay City-Midland, MI MSA	41	1	-2.236	-2.149	-1.964	-2.087	-3.508

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 Housing-Cost Measure	Cobb-Douglas Land Only Average (1)	Cobb-Douglas Const Cost Average (2)
Land-Value Differential	2.005 (0.177)	2.109 (0.184)
Construction-Cost Differential		-0.342 (0.437)
Geographic Constraint Index: z-score	-0.015 (0.047)	0.013 (0.048)
Regulatory Index: z-score	-0.017 (0.053)	All Subindices
Constant	0.000 (0.043)	-0.001 (0.038)
Number of Observations	189	183
Adjusted R-squared	0.759	0.772
Implied Land-Cost Share	0.499 (0.044)	0.474 (0.041)
Implied Material-Cost Share		0.162 (0.200)

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 A5: MODEL OF HOUSING-COST DETERMINATION BY YEAR

Specification	Restricted Translog 2007	Restricted Translog 2008	Restricted Translog 2009	Restricted Translog 2007-2009	Restricted Translog 2007	Restricted Translog 2008	Restricted Translog 2009	Restricted Translog 2007-2009
Dependent Variable	Hous. Cost (1)	Hous. Cost (2)	Hous. Cost (3)	Hous. Cost (4)	Hous. Cost (5)	Hous. Cost (6)	Hous. Cost (7)	Hous. Cost (8)
Land-Value Differential	0.212 (0.020)	0.202 (0.023)	0.215 (0.031)	0.226 (0.040)	0.183 (0.028)	0.184 (0.026)	0.192 (0.031)	0.228 (0.034)
Construction-Cost Differential	0.788 (0.020)	0.798 (0.023)	0.785 (0.031)	0.774 (0.040)				
Construction-Wage Differential					0.817 (0.028)	0.816 (0.026)	0.808 (0.031)	0.772 (0.034)
Land-Value Differential Squared	0.082 (.032)	0.096 (.042)	0.141 (.037)	-0.020 (.071)	0.023 (.053)	0.078 (.044)	0.112 (.042)	0.010 (.053)
Construction-Cost Differential Squared	0.082 (.032)	0.096 (.042)	0.141 (.037)	-0.020 (.071)				
Construction-Wage Differential Squared					0.023 (.053)	0.078 (.044)	0.112 (.042)	0.010 (.053)
Land-Value Differential X Construction-Cost Differential	-0.164 (.064)	-0.192 (.084)	-0.282 (.074)	0.040 (.142)				
Land-Value Differential X Construction-Wage Differential					-0.046 (.106)	-0.156 (.088)	-0.224 (.084)	-0.020 (.106)
Geographic Constraint Index: z-score	0.070 (0.016)	0.064 (0.016)	0.053 (0.019)	0.084 (0.024)	0.071 (0.017)	0.072 (0.014)	0.060 (0.022)	0.085 (0.021)
Regulatory Index: z-score	0.046 (0.011)	0.033 (0.011)	0.048 (0.015)	0.051 (0.014)	0.053 (0.013)	0.046 (0.012)	0.065 (0.012)	0.057 (0.015)
Constant	-0.021 (0.017)	-0.019 (0.017)	-0.035 (0.019)	0.007 (0.024)	-0.006 (0.016)	-0.016 (0.016)	-0.028 (0.019)	-0.003 (0.024)
Number of Observations	122	122	122	183	128	128	128	189
Adjusted R-squared	0.778	0.723	0.700	0.852	0.768	0.717	0.698	0.854
Elasticity of Substitution	0.508 (0.176)	0.408 (0.237)	0.166 (0.165)	1.112 (0.462)	0.848 (0.340)	0.482 (0.260)	0.275 (0.217)	0.946 (0.341)

Robust standard errors, clustered by CMSA, reported in parentheses. Data sources as described in Table 2.

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

Specification Dependent Variable	Restricted Translog Residential Land Only Hous. Cost (1)	Restricted Translog Raw Land Differentials Hous. Cost (2)	Restricted Translog Residential Land Only Hous. Cost (3)	Restricted Translog Raw Land Differentials Hous. Cost (4)
Land-Value Differential	0.204 (0.042)	0.186 (0.024)	0.207 (0.034)	0.185 (0.022)
Construction-Cost Differential	0.796 (0.042)	0.814 (0.024)		
Construction-Wage Differential			0.793 (0.034)	0.815 (0.022)
Land-Value Differential Squared	0.069 (.027)	-0.069 (.027)	0.077 (.021)	-0.046 (.022)
Construction-Cost Differential Squared	0.069 (.027)	-0.069 (.027)		
Construction-Wage Differential Squared			0.077 (.021)	-0.046 (.022)
Land-Value Differential X Construction-Cost Differential	-0.138 (.054)	0.138 (.054)		
Land-Value Differential X Construction-Wage Differential			-0.154 (.042)	0.092 (.044)
Geographic Constraint Index: z-score	0.087 (0.022)	0.075 (0.021)	0.091 (0.020)	0.075 (0.019)
Regulatory Index: z-score	0.061 (0.017)	0.065 (0.011)	0.068 (0.018)	0.070 (0.012)
Constant	0.022 (0.021)	0.042 (0.021)	0.017 (0.022)	0.028 (0.020)
Number of Observations	178	183	184	189
Adjusted R-squared	0.845	0.862	0.845	0.866
Elasticity of Substitution	0.575 (0.126)	1.455 (0.185)	0.530 (0.097)	1.303 (0.149)

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.