Hedonic, Residual, and Matching Methods for Residential Land Valuation

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Abstract

Accurate estimates of land values on a property-by-property basis are an important requirement for the effective implementation of land-based property taxes. We compare hedonic, residual, and matching techniques for mass appraisal of residential land values, using data from Maricopa County, Arizona. The first method involves a hedonic valuation model estimated for transactions of vacant lots. The second approach subtracts the depreciated cost of improvements from the value of improved properties to obtain land value as a residual. The third approach matches the sales of vacant lots with subsequent sales of the same properties once they have been developed. For each pair, we use a land price index to inflate the land price to the time of the improved property transaction and then calculate land leverage (the ratio of land to total property value). A hedonic model is estimated and used to predict land leverage for all improved properties. We conclude that the matching approach is the most promising of the methods considered.

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1. Introduction

Land valuation is important for multiple reasons. It is central to land taxation, two-rate taxation of land and buildings, and the taxation of land value increments. Decomposing the value of properties into their land and structure components is also important for understanding house price dynamics (Bostic *et al.*, 2007; Bourassa *et al*., 2009; Zhou and Haurin, 2010; Knoll *et al*., 2017) and understanding the role of land price changes over time (Bourassa *et al*., 2011; Diewert *et al*., 2015; Davis *et al*., 2017; Davis *et al*., 2021). However, it has proven extraordinarily challenging to estimate land values for improved properties in an efficient and accurate manner. Holland (1970) devoted an entire book of edited papers to this topic and the Lincoln Institute of Land Policy has continued to address this issue by supporting research on the topic (*e.g.*, Netzer, 1998; Bell *et al*., 2009). As one of the contributors to Holland (1970) observed, “any conception that the valuation of land is a simple and easy process is founded on pure illusion” (Back, 1970, p. 54).

Our aim is to explore the usefulness of hedonic, residual, and matching techniques for estimating residential land values. For that purpose, we use vacant land and improved single-family property sales data as well as the full roster of single-family properties from Maricopa County, Arizona. To be cost-effective, methods need to be accurate and reasonably easy to apply in a mass appraisal context. Hence our emphasis is on automated valuation techniques that are sufficiently straightforward to be applied by a typical urban county property appraiser’s office and we do not consider more complex approaches such as machine learning (for examples of the latter, see Mayer *et al*., 2019).

Hedonic models are widely used in the context of property valuation, especially residential property valuation (for a review, see Malpezzi, 2003). Information about a sample of properties that transacted is used to estimate models that can predict the values of out-of-sample properties that did not transact. Hedonic models are a valuable tool for property tax appraisers, mortgage underwriters, valuation firms, and regulatory authorities. Popular online resources, such as Zillow.com in the United States, rely on such models to provide regularly updated estimates of property values.

In addition to their use for valuation of improved properties, hedonic models can also be used for land valuation. Hedonic models of improved properties have been used to infer land values (*e.g.*, Wentland *et al*., 2020), but this is problematic because the estimated coefficients for some variables may reflect the influence of both land and improvement characteristics.[1] For example, the intercept terms and time dummies in hedonic models for improved properties relate to both land and improvements. Moreover, we show that most hedonic coefficients for land-related variables for improved properties differ significantly from those for vacant land.

In practice, the estimation of such models is hampered by insufficient transactions pertaining to vacant and redevelopment land in the more central locations of cities, even though the overall sample of land sales for a metropolitan area may be quite large.[2] The Phoenix MSA sample used by Nichols *et al*. (2013) contains 18,249 land sales (8,472 commercial and 9,777 residential) for 1995 to 2011, but these are unlikely to be distributed evenly over space and time due to uneven geographic patterns of development as well as economic cycles. Gedal and Ellen (2018), for instance, report that vacant parcels in New York City sold between 2003 and 2009 were disproportionately located in distressed neighborhoods. To address the issue of the paucity of vacant land transactions and obtain a sample that would be more uniformly distributed across space, several papers have focused on using data from teardown values (prices paid for properties purchased for demolition and redevelopment). Been *et al*. (2009) use teardown values to measure land price changes in New York, following an approach suggested by Rosenthal and Helsley (1994) and extended by Dye and McMillen (2007). Using data for New York City, Gedal and Ellen (2018) conclude that teardown parcels appear to be more representative of the city as a whole and may be a more useful approach to developing estimates of land prices, at least in the central cities of large urban areas.[3]

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[1] In a variation on this approach, Sunderman and Birch (2002) combine improved property and vacant land transactions in the same model.

[2] As Netzer (1998, p. 116) observed: "The problem today, as in the past, lies in the wholly unsatisfactory data on land values …."

[3] There are very few teardowns in the Maricopa County data, meaning that the approach used by Gedal and Ellen (2018) cannot be applied.

The residual approach, which subtracts an appraised value of the structure from total property value to yield land value, is not commonly used as a mass appraisal technique for residential land. However, it has been used in the context of estimating land leverage—*i.e.*, the ratio of land value to overall property value—and for land price index construction. Davis and Palumbo (2008), for instance, focus on 46 large U.S. metropolitan areas and show that land leverage for single-family owner-occupied homes increased from an average of 32 percent in 1984 to 51 percent in 2004. The authors price the housing stock in each area using depreciated construction costs applied to property characteristics contained in the American Housing Survey (AHS) for a benchmark year. Land value is the total property value reported in the AHS less the depreciated value of the structure. Bourassa *et al*. (2011) use a similar approach to extract land values from transaction prices for single-family homes in Switzerland. The authors use hedonic models to develop time series of land prices and land leverage. Davis *et al*. (2017) use property-level data to estimate the price of land for detached single-family homes in the Washington, DC metropolitan area. They measure the value of land for newly built homes as the difference between the sale price and estimated construction cost for the structure. Davis *et al.* (2021) use Federal Housing Finance Agency (FHFA) appraisal data, which allow them to estimate land leverage and land values for census tracts throughout the U.S. They find that the residual method works well for about the first 20 years of the life of the structure and, consequently, base their estimates on properties with relatively new structures. One issue with implementing the residual method in a mass appraisal context is that information about the characteristics of structures is unlikely to be as detailed or precise as one would like. Also, assumptions about construction costs and depreciation rates may be inaccurate.

Our third approach involves matching vacant land sales with subsequent transactions once those parcels have been developed.[4] For each pair of sales, the value of the structure is calculated as the improved sale price minus the historical land price inflated over the period between the vacant land and improved property transactions. This approach allows us to compute land leverage for each matched improved property, which is then used as the dependent variable in a model containing property characteristics as independent variables. The estimates from this

[4] Previous research has used a matching method to calculate the elasticity of substitution between land and capital (Thorsnes, 1997; Ahlfeldt and McMillen, 2018).

model are used to predict land leverage for other properties.[5] One potential limitation of this approach is that the matched properties may not be representative of all properties. Also, the application of this method to markets other than Maricopa County depends on the availability of vacant land transactions that can then be matched to subsequent sales of improved properties.[6]

We compare hedonic, residual, and matching methods for valuing single-family residential land. Our hedonic approach focuses on vacant land transactions, using data for the entire county as well as one submarket with a relatively large number of land sales. We conclude that this method does not perform well within sample and, hence, would be inaccurate as a means for out-of-sample prediction. We also show that a hedonic model of improved properties cannot be used to infer land values. We then apply the residual approach to improved properties that transacted and also conclude that the within-sample performance is less than satisfactory. Finally, we implement our third method by matching vacant land and subsequent improved property transactions, calculating the land leverage ratio, and then estimating a model with that ratio as dependent variable. We then use that model to predict land leverage for all other single-family properties. Although previous research has matched vacant land transactions with subsequent sales once the land has been improved (Bostic *et al*., 2007), we believe this paper is the first to then use a land leverage regression model to predict land leverage for every single-family property in a market. We conclude that this method yields reasonable estimates of land value and has potential for practical application.

The remainder of the paper is structured as follows. We next discuss our methods before turning to a description of the Maricopa County data. The penultimate section presents our results, while the final section concludes.

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[5] It has been suggested that a real options approach might be useful in this context; however, Clapp *et al.* (2013) and Munneke and Womack (2020) find that including measures of real option values in hedonic models has little or no effect on explanatory power.

[6] Such data may be available on a case-by-case basis for individual jurisdictions in the U.S. but, to our knowledge, are not available in any national database.

2. Methods

We first apply the hedonic technique to vacant land transactions for the entire county and for a submarket. We limit the county-wide analysis to an ordinary least squares (OLS) estimation, but also experiment with a spatial model and a robust technique when analyzing the submarket data. We further compare the land-related coefficients estimated for the land transactions model with those estimated for a model of improved properties to assess whether the latter model could be used to infer land values.

To test the accuracy of hedonic predictions, we rely in part on criteria set by the International Association of Assessing Officers (IAAO, 2013), which focus on within-sample accuracy. We calculate the coefficient of dispersion (COD), which is the mean absolute difference between the ratios of assessed values and sale prices and the median ratio. We also calculate the price-related differential (PRD), which is the mean assessment ratio divided by the weighted mean ratio. The weighted mean ratio is the value-weighted average of the assessment ratios in which the weights are the sale prices.[7] For land assessments, the IAAO COD standard is between 0.05 and 0.25. High CODs (> 0.25) indicate excessive horizontal variability (*i.e.*, variation across properties) in assessment accuracy. The PRD should be between 0.98 and 1.03 according to the IAAO. As a measure of vertical equity, PRD values higher than 1.0 indicate regressivity, while those below 1.0 indicate progressivity. Regressivity refers to higher valued properties having lower assessment ratios than lower valued properties, while progressivity is the reverse. We supplement these measures with others commonly found in the literature: the mean absolute error (MAE), mean absolute percentage error (MAPE), and percentages of valuations within 10 and 20 percent of the sale prices, respectively. Note that the COD and MAPE statistics are, for all practical purposes, measuring the same thing.[8]

We then focus on submarkets with the aim of identifying one that has a relatively large number of vacant land transactions that are distributed across the neighborhoods within the submarket, allowing us to use neighborhood dummy variables without the risk of over-fitting. We identify such a submarket—Market 26, located southeast of Tempe—that was rapidly

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[7] The weighted mean ratio is equivalent to the average assessed value divided by the average sale price.

[8] If the COD were defined in terms of the mean rather than the median ratio, it would be the same as the MAPE.

developing during the period of study and consequently had many vacant land sales. We estimate a hedonic model, which we use to assess within-sample prediction accuracy and to predict land values for improved properties within that submarket. Our assumption is that, if hedonic techniques do not work well in such a submarket, then they are unlikely to work in submarkets with fewer vacant land transactions. As mentioned above, we experiment with spatial and robust models to find out if they yield more accurate results. We estimate both spatial autoregressive (SAR) and spatial error (SEM) models (Anselin, 2003). The spatial weights matrix for these models is based on the five nearest neighboring transactions that occurred within the same calendar year, weighted by the inverse of distance from each property. Robust estimation techniques are designed to reduce the influence of outliers by down weighting observations based on the size of their residuals (Andersen, 2008; Heritier *et al*., 2009; Bourassa *et al*., 2013). In contrast, OLS minimizes the sum of squared errors, which means that large outliers can have a disproportionate influence on the resulting estimates. We use a robust M estimation method that gives decreasing weights to observations with larger standardized residuals (Huber, 1964).[9]

We also focus on Market 26 for testing the residual method. We implement that approach using RS Means (2018) construction costs applied to improved property transactions. The RS Means costs allow us to value the primary structure as well as outbuildings and most other improvements on the property. For some types of improvements, such as tennis courts, we had to estimate costs using other sources. We first calculated new construction costs and then adjusted for depreciation. We reviewed empirical work on depreciation of single-family properties (*e.g*., Harding *et al*., 2007; Bourassa *et al*., 2011) but selected the depreciation rates published by RS Means (2018) because they allow for different rates for different quality levels. We subtract the depreciated cost estimates from transaction prices to yield residual land values.[10]

We then switch to the matching method. Vacant land sales are paired with subsequent sales of the same properties after they have been improved. The land sale prices are inflated using a hedonic land price index to values contemporaneous with the improved property

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[9] Other methods that might be preferred (S or MM) would not converge for our data; see Bourassa *et al*. (2016) for technical details about these methods.

[10] Applying the residual method to all residential properties would involve subtracting cost estimates from assessed improved values for those properties that did not transact.

transactions (details are provided in Section 4.4). The land leverage ratio is calculated for each matched property and then a hedonic equation is estimated with that ratio on the left-hand side and a set of characteristics on the right-hand side. We then estimate land leverage for all single-family properties in the county.[11]

3. Data

The data are arm's-length transactions from the Maricopa County Assessor's Office. We use vacant land sales for the period 2000 through 2018. The vacant land transactions were limited to properties zoned for single-family use and designated as either vacant land or single family in the affidavit of sale. We use improved property transaction data for 2007 through 2018. Here we restricted the data to properties zoned for single-family use, assigned a single-family land use code, and designated as single family in the affidavit of sale. We also used the full population of single-family properties for 2007 to 2018.[12] This set of properties was limited to those zoned for single-family use and assigned a single-family land-use code.[13] We excluded any vacant land or improved property transactions that involved more than one parcel.

The datasets include a range of variables relevant to land values: location (latitude and longitude), lot size, zoning category, market areas, neighborhoods, and flood zone details. Other measures are provided for some observations but were frequently missing in the land sales dataset or were generally not available in the improved sales datasets, so could not be used to predict land values for improved properties. The improved transaction and full property roll datasets include livable floor area, a quality classification, year of construction (weighted to account for additions), and floor areas of other parts of the structure, such as garages and basements. In addition, there are measures of the sizes of swimming pools and spas, various

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[11] Land values could then be estimated by multiplying the land leverage estimate by the assessed value of the property.

[12] Maricopa County identifies the full property rolls by the year in which the property tax is levied, rather than the year from which the data were drawn. For example, the full property roll for 2018 is labeled 2020. To avoid confusion, we refer here to the year of the data rather than the year of the tax assessment.

[13] Properties zoned for a mix of single-family and other uses were also excluded from the improved property transactions and full property roll datasets.

types of outbuildings, and tennis and other sports courts. No information is provided regarding the number of rooms in the house or the numbers of rooms of particular types, such as bathrooms. In regard to bathrooms, the data include the number of fixtures (sinks, toilets, bathtubs, etc.).

We deleted some observations because key variables (such as latitude and longitude) had missing values. In other cases, we were able to assume that missing values meant that the property did not have the relevant feature, or we were able to infer a value based on the values provided for other variables (an example is the flood zone variables). Preliminary analysis of the data indicated that outliers were problematic in several respects. Consequently, throughout the analysis, we deleted properties with land area in the lower or upper one percent of the distribution of that variable for the full population of single-family properties. Also, for improved transactions, we deleted properties with sale prices or prices per square foot in the upper or lower one percent of the distribution. Finally, we deleted properties with land leverage in the upper or lower one percent. Table 1 gives the time periods and sample sizes for our analyses.[14] For comparison purposes, Appendix Table A1 provides means for land and location characteristics across three of the samples: Maricopa County vacant land sales, Maricopa County improved property sales, and Market 26 vacant land sales (all for 2015-2018).

[14] We chose a four-year window for most of our samples so that we would have enough data for estimation purposes while avoiding the risk of significant changes in model parameters. For the other samples, it was appropriate to specify larger windows.

Table 1

Samples and sample sizes.

Model	Time period	Sample size
Maricopa County vacant land sales for hedonic valuation	2015-2018	6,982
Market 26 vacant land sales	2015-2018	653
Market 26 improved property sales	2015-2018	31,981
Market 26 newly improved property sales	2015-2018	8,167
Maricopa County improved property sales	2015-2018	288,204
Maricopa County vacant land sales for land price index	2000-2018	48,256
Maricopa County matched vacant land and improved sales	2007-2018	10,224
Maricopa County improved property sales	2007-2018	786,629
Maricopa County improved properties	2007-2018	11,156,277

Multiple variables were transformed for estimation purposes. Natural logarithms of transaction prices, land area, and floor area were used, and categorical variables, such as market area, were converted to dummy variables (as in Bourassa *et al*., 2003). The transformation of transaction prices adjusts for skewness in the data, while the transformations of the area variables reflect diminishing returns to size.[15] The value of personal property included in the transaction was deducted from the sale price. Construction year was converted to age by subtracting it from the year of the transaction. We combined similar zoning categories into a smaller set of dummy variables and converted the square foot measures for outbuildings, pools, and spas into dummy variables for the purposes of hedonic modeling (although the original square foot measures were used for depreciated cost calculations). We determined whether lots could be subdivided in those cases where the zoning specified a minimum lot size and created a dummy variable equal to one for subdivisible properties. The bathroom fixtures measure was divided by three to approximate the number of bathrooms. The latitude and longitude variables were used to calculate distances to the central business district as well as the distances used to construct spatial weights matrices used for the spatial model.

As mentioned above, we use RS Means (2018) construction cost estimates for the residual analysis. RS Means provides detailed costs per square foot that cover most of the types

[15] Following Duan (1983), predicted values were calculated as $\hat{y}_i = \exp^{\left(\ln y_i + s^2/2\right)}$ where *s* is the root mean square error (or equivalent statistic for the spatial and robust estimations).

of improvements for which we have variables in the transactions data. These estimates are provided for different quality classes, which were assigned to the quality classes defined by Maricopa County as shown in Table 2. For the main structure, we have four quality categories, three categories for numbers of stories, and 10 size categories, yielding a total of 120 different prices per square foot. We first calculate the cost of new construction and then adjust for depreciation based on quality class. We apply geometric depreciation rates calibrated to be consistent with cumulative depreciation rates after 50 years as provided by RS Means (Table 2).[16]

Table 2

Correspondence between Maricopa County and RS Means quality classes and depreciation rates.

Maricopa County quality class	RS Means quality class	Annual geometric depreciation rate	Cumulative depreciation after 50 years
0, 1, or 2	Economy	2.08%	65%
3 or 4	Average	1.38%	50%
5	Custom	1.02%	40%
6 or 7	Luxury	1.02%	40%

Note: Based on descriptions of quality classes provided by Maricopa County and RS Means (2018).

4. Results

4.1. Land sales hedonic models

We first estimate a county-wide hedonic model for vacant land sales for the period 2015-2018. As shown in Table 3, that model produces relatively inaccurate predictions, with a COD well above the maximum 25.0 recommended by the IAAO.[17] The PRD statistic is also well above the target range, implying regressivity or under-assessment of higher-valued properties relative to lower-valued ones. Moreover, the county-wide model performs poorly with respect to the percentage of predictions within 10 percent of the sale price; a rule-of-thumb target for that

[16] Use of geometric rates prevents depreciation for older houses from exceeding 100 percent.

[17] The regression results for the county-wide land sales model are shown in Appendix Table A1.

metric is a minimum percentage of 50 percent (see, *e.g.*, Fik *et al*., 2003). We expect that this model would perform even worse if used to predict land values out-of-sample.[18]

Table 3

Prediction accuracy measures for land sales hedonic models, 2015-2018.

Model	Coefficient of dispersion (COD)	Price-related differential (PRD)	Mean absolute error (MAE)	Mean absolute percentage error (MAPE)	Percentage of predictions within 10% of price	Percentage of predictions within 20% of price
Maricopa County vacant land sales model (OLS)	59.5	1.47	82,043	72.7	15.4	28.9
Market 26 vacant land sales model (OLS)	24.2	1.12	47,805	25.9	32.5	58.3
Market 26 vacant land sales model (SEM)	25.2	1.13	49,125	26.1	32.9	55.3
Market 26 vacant land sales model (robust M)	24.0	1.14	45,962	24.2	36.9	61.6

Note: N=6,982 for Maricopa County and N=653 for Market 26. Targets set by the IAAO (2013) are $5.0 \leq \text{COD} \leq 25.0$ (for vacant land) and $0.98 \leq \text{PRD} \leq 1.03$ (for all property types). Appendix Table A2 reports the regression results for these four models.

We then identify the submarket with the largest average number of vacant land transactions per neighborhood (Market 26). We first estimate an OLS version of the model which, as shown in Table 3, performs better than the county-wide model, although the COD is just barely within the acceptable range. The PRD statistics and the percentage of predictions within 10 percent of the actual price remain unsatisfactory.

We then experiment with spatial autoregressive (SAR) and spatial error (SEM) models. The coefficient for the spatial error term is significant in the SEM model, while that for the spatial lag term is not significant in the SAR model, indicating spatial autocorrelation with respect to only the error term. However, the performance of the SEM model is slightly worse

[18] As Downing (1970, p. 123) concluded regarding his hedonic analysis of residential land values in Milwaukee: “The predictive power of this technique was much less than was hoped for.” It seems that not a lot of progress has been made in 50 years.

than that of the OLS model. Finally, the robust estimation yields a slightly better COD than the OLS estimation, but the other statistics remain unsatisfactory.

4.2. Comparison of land-related coefficients in land and improved property hedonic models

We compare the estimated coefficients for land-related variables from county-wide land sales and improved property sales models for 2015-2018. This is to assess whether the coefficients for land-related variables from an improved property hedonic model could be used to infer underlying land values. We assess the significance of the differences in coefficients by combining vacant land and improved property sales in a single data set. We include a set of land and location characteristics interacted with a dummy variable for vacant land transactions and use the *t* statistics on those estimates to assess the statistical significance of differences in coefficients for vacant land and improved properties. Of the coefficients for the 39 variables that relate specifically to land value (including the submarket dummies), 33 differ between the two models at the 0.01 level or better, while two others differ at the 0.05 level or better (see Appendix Table A3). Clearly, the land-related coefficients estimated for vacant land sales are not the same as those for improved property sales. A comparison of the means for land and location characteristics of vacant and improved parcels (see Appendix Table A1) suggests that this might be due to significant differences in the samples, related to factors such as parcel size, zoning, and location.

4.3. Residual land value estimates

We then calculate depreciated replacement costs to estimate the value of improvements and residual land values for houses that sold between 2015 and 2018 in Market 26. These are compared with land values estimated for this sample of improved properties using the OLS hedonic model of vacant land sales for Market 26 reported in Appendix Table A2. We also calculate residual improvement values by subtracting the predicted land values from the transaction prices. The mean land values are similar for the two methods (Table 4), but the residual method produces negative values for about four percent of the properties, including some improbably large negative values.[19] This suggests that the residual method is less accurate than the hedonic method; however, as we have seen, the hedonic method itself is not particularly accurate within the sample of vacant land sales and so is presumably even less accurate when applied to improved properties. Table 4 also highlights another problem with the hedonic land value predictions, namely that in some cases they imply large negative improvement values.

Table 4

Comparison of residual and hedonic results, improved property transactions, Market 26, 2015-2018.

Method	Mean	Median	Standard deviation	Minimum	Maximum
Land values calculated using residual method	95,368	79,705	79,824	-197,947	721,090
Improvement values estimated using depreciated cost method	265,672	254,565	79,615	28,988	1,276,058
Land values predicted from vacant land sales hedonic model (see note)	101,813	91,416	51,583	9,567	789,258
Improvement values calculated as residual using vacant land sales hedonic model	259,227	239,967	98,976	-192,673	1,046,780

Note: *N*=31,981. The vacant land sales hedonic model is the OLS model for Market 26 reported in Appendix Table A2.

To test whether the results from the residual method are affected by assumptions about depreciation, we focused on new properties (*i.e.*, for which the age of the building is zero).[20] This did not alter the results substantially, as 3.5 percent of the land value estimates are negative and some of these are large in absolute value (Table 5). This suggests that there are issues other than the depreciation assumptions. Inspection of the properties with negative land values did not reveal any obvious patterns that might help to explain these results.

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[19] Small negative values are possible when the structure is a teardown, reflecting the cost of demolition, but large negative values are implausible.

[20] We note Welch's (1982, p. 92) observation that "residually derived land values are generally considered highly reliable only when the improvements are totally depreciated or not depreciated at all."

Table 5

Comparison of residual and hedonic results, recently improved property transactions, Market 26, 2015-2018.

Method	Mean	Median	Standard deviation	Minimum	Maximum
Land values calculated using residual method	100,750	83,658	83,612	-168,300	721,090
Improvement values estimated using depreciated cost method	291,746	280,462	66,039	183,125	711,947
Land values predicted from vacant land hedonic model (see note)	95,908	86,440	43,432	12,977	500,554
Improvement values calculated as residual using vacant land sales hedonic model	296,588	273,967	92,471	46,571	1,010,836

Note: *N*=8,167. The vacant land sales hedonic model is the OLS model for Market 26 reported in Appendix Table A2.

4.4. Matching approach

Next, we match sales of vacant land parcels with subsequent sales of the same properties after they have been improved. For this purpose, we use the sample of land sales for 2000 to 2018 and improved property sales for 2007 to 2018.[21] For land parcels that sold more than once, we choose the most recent transaction. Similarly, for improved properties that sold more than once, we select the earliest transaction. This minimizes the amount of time between the vacant land transaction and the improved property transaction. This yields 10,224 paired transactions.

We then create a land price index by estimating a county-wide hedonic model for vacant land transactions with quarterly time dummies for 2000 to 2018. This model has the same set of variables as in the land sales model shown in the Appendix, including dummy variables for submarkets. The index (Fig. 1) shows a dramatic pattern of boom and bust, with a 278 percent increase between 2000 and 2006 followed by a decline to 90 percent of the 2000 level in 2009. As expected, land prices are significantly more volatile than house prices. This index is then used to inflate the land prices to the time of the corresponding improved property transactions. The land leverage ratio is calculated by dividing land value by total property value. Then land leverage is regressed on various property characteristics as shown in Table 6. Generally, the

[21] In other words, we used all of the data provided by Maricopa County.

coefficients have the expected signs in those cases where these could be predicted a priori. For example, the coefficient on distance to the CBD is negative, reflecting greater land leverage in central locations, and that on age of the structure is positive, due to the impact of depreciation.

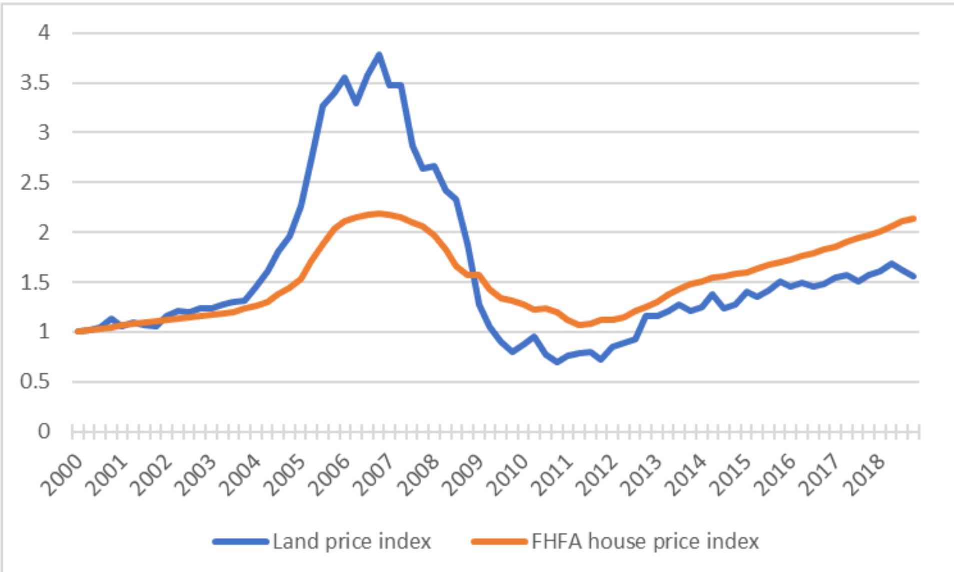

Fig. 1. Land price index for Maricopa County and house price index for Phoenix-Mesa-Chandler MSA, 2000-2018.

Note: 2000Q1=1. The land price index was created using a hedonic model with quarterly time dummies and based on vacant land transactions (*N*=48,256). The house price index is from FHFA (www.fhfa.gov) and includes Pinal County as well as Maricopa County.

Table 6

Results from regressing land leverage on property characteristics, Maricopa County matched sample, 2007-2018.

Variable	Estimate
Intercept	0.324 (0.020)***
Distance to CBD	-0.002 (0.000)***
Zoning	
Planned development	0.042 (0.018)**
Town house	0.030 (0.025)

Variable	Estimate
Min. lot size 4,000 to 9,000 sq. ft.	0.061 (0.018)***
Min. lot size 10,000 to 24,000 sq. ft.	0.061 (0.018)***
Min. lot size 30,000 to 35,000 sq. ft.	0.070 (0.018)***
Min. lot size one acre	0.062 (0.018)***
Min. lot size 70,000 to 190,000 sq. ft.	0.058 (0.020)***
Submarket	
2	0.005 (0.009)
3	-0.007 (0.010)
4	-0.047 (0.009)***
5	0.018 (0.008)**
6	-0.007 (0.015)
7	0.005 (0.007)
8	0.004 (0.008)
9	-0.029 (0.007)***
10	-0.033 (0.026)
11	-0.011 (0.008)
13	0.008 (0.014)
14	0.090 (0.011)***
15	-0.006 (0.008)
16	-0.025 (0.010)**
17	-0.067 (0.011)***
18	0.049 (0.011)***
19	0.014 (0.021)
20	0.017 (0.007)**
21	-0.100 (0.064)

Variable	Estimate
22	-0.155 (0.018)***
23	-0.051 (0.010)***
24	0.015 (0.007)**
25	-0.048 (0.008)***
26	0.023 (0.007)***
27	-0.033 (0.011)***
Floor area ratio	0.058 (0.014)***
Improvement class	
4	-0.016 (0.003)***
5	-0.037 (0.004)***
6	-0.046 (0.005)***
7	-0.038 (0.017)**
Age	0.001 (0.000)***
RV garage	-0.027 (0.005)***
Storage shed	-0.018 (0.005)***
Pool	-0.018 (0.002)***
Spa	-0.011 (0.004)**
Year	
2008	-0.010 (0.005)**
2009	-0.123 (0.004)***
2010	-0.128 (0.004)***
2011	-0.140 (0.005)***
2012	-0.125 (0.005)***
2013	-0.117 (0.005)***
2014	-0.121 (0.005)***

Variable	Estimate
2015	-0.111 (0.005)***
2016	-0.113 (0.005)***
2017	-0.100 (0.005)***
2018	-0.105 (0.005)***
N	10,224
R-squared	0.245
Adjusted R-squared	0.241

Note: Standard errors in parentheses (). *** indicates significance at the 1 percent level; ** indicates significance at the 5 percent level; * indicates significance at the 10 percent level.

We then use the regression results to estimate land leverage for the full set of improved single-family properties for each year from 2007 through 2018 (Table 7). Mean land leverage declined from 2007 through 2011, reflecting the housing market bust. Since 2011, the trend has been upwards. The minimum and maximum values also follow this pattern and reflect plausible ranges of values. Fig. 2 compares our land leverage estimates with those of Davis *et al.* (2021), who used proprietary FHFA single-family appraisal data. Our results are remarkably similar to theirs for the seven years of overlapping data. Fig. 3 maps the mean land leverage ratios by neighborhood for 2018, displaying an expected pattern of high leverage closer to the Phoenix CBD and low leverage in more peripheral locations. Overall, the results suggest that the matching method could be used effectively for mass appraisal of residential land values. However, it would be useful to conduct appraisals of a sample of properties to verify the accuracy of the estimates of land leverage and implied land values.[22]

[22] One potential issue with our approach is that we estimate our model for properties with relatively young structures, but then predict land leverage for properties of all ages. Davis *et al.* (2021) also focus on relatively young structures. In practice, it may be possible to expand the period for the matched sample, enabling more accurate estimation of the effect of age on land leverage. The matched sample also differs from the full set of single-family properties due to the former's larger average lot size, minimum

Table 7

Predicted land leverage for all single-family properties, Maricopa County, 2007-2018.

Year	*N*	Mean	Standard deviation	Minimum	Maximum
2007	880,401	0.365	0.046	0.157	0.590
2008	887,901	0.356	0.046	0.148	0.582
2009	868,097	0.243	0.046	0.036	0.470
2010	969,915	0.233	0.046	0.033	0.461
2011	969,915	0.221	0.046	0.021	0.450
2012	906,956	0.243	0.046	0.038	0.473
2013	915,347	0.252	0.047	0.048	0.482
2014	924,482	0.249	0.047	0.045	0.479
2015	934,551	0.259	0.046	0.056	0.485
2016	947,694	0.256	0.046	0.055	0.484
2017	969,915	0.270	0.046	0.070	0.499
2018	981,103	0.265	0.046	0.066	0.495

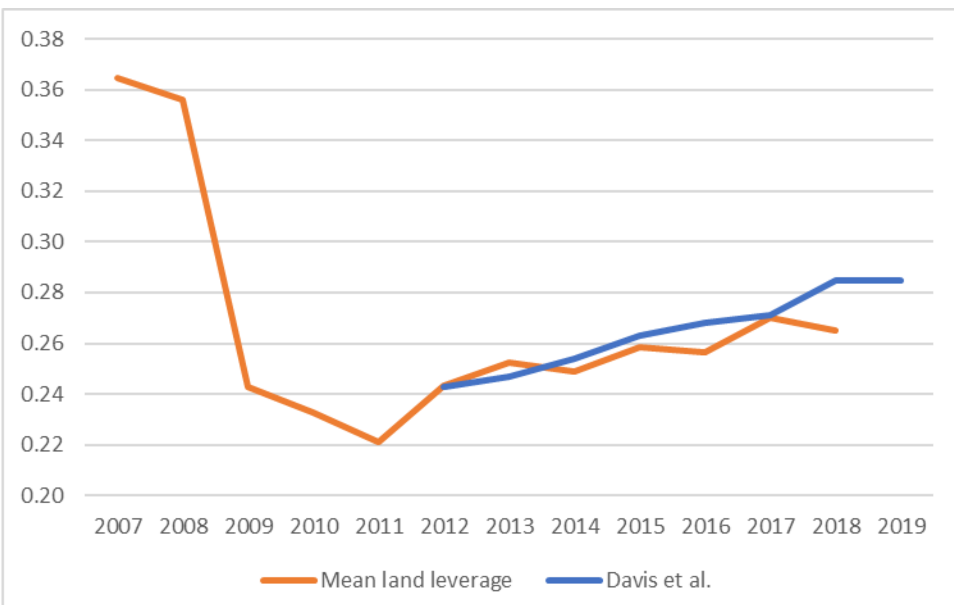

Fig. 2. Comparison of our land leverage estimates with those of Davis *et al*. (2021), single-family properties, Maricopa County.

zoned lot size, distance from the CBD, and floor area, as well as substantially younger average age of structure.

Note: We estimate land leverage for all single-family properties (with the exception of outliers), while Davis *et al.* focus on selected appraised properties with structures no more than 15 years old.

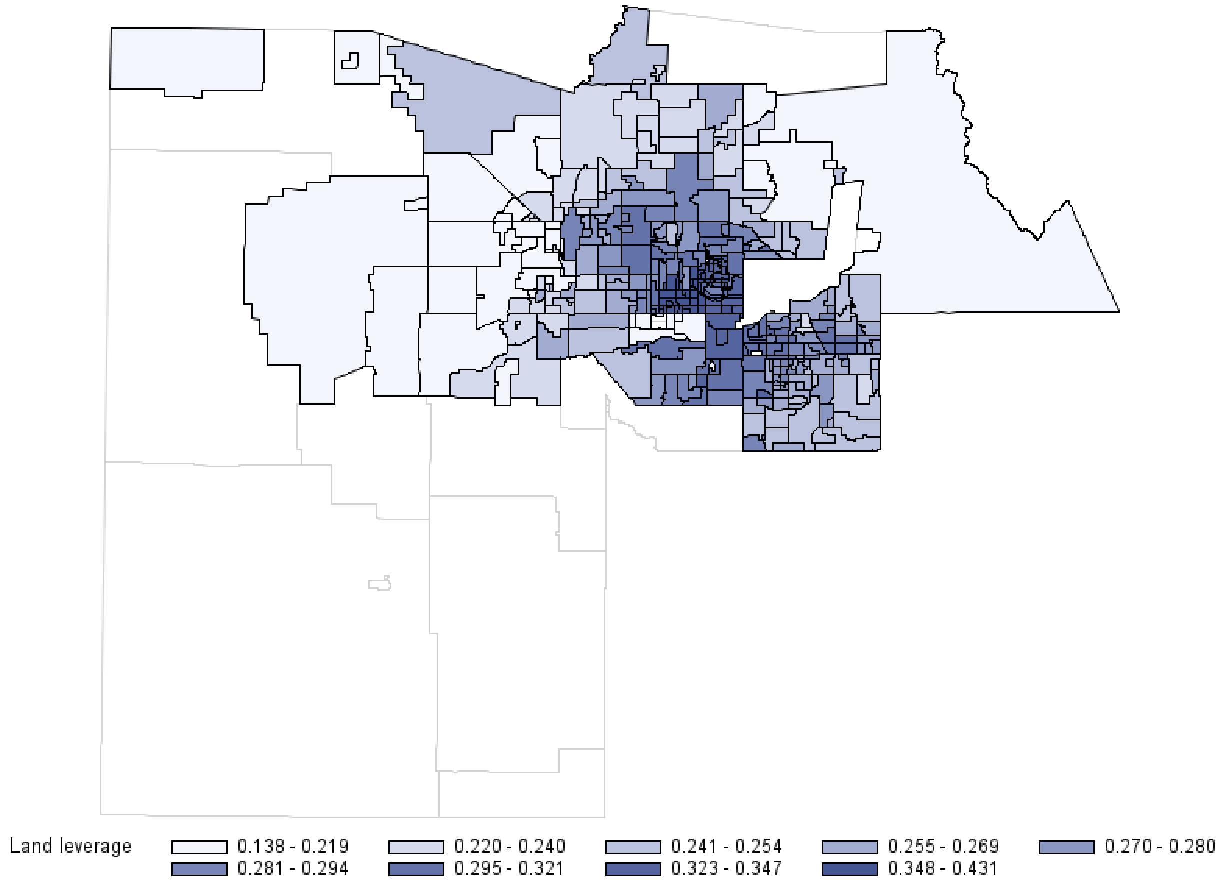

Fig. 3. Land leverage by neighborhood, Maricopa County, 2018.

Note: Land leverage was not estimated for the unshaded areas due to either a lack of matched vacant and improved property transactions or small numbers of improved properties. In practice, it may be possible to combine neighborhoods to overcome this issue at least partly.

5. Conclusions

We explore multiple approaches for mass appraisal of land values for improved single-family residential properties: predictions based on a hedonic regression model of vacant land transactions; estimates derived by subtracting the depreciated costs of improvements from transaction prices of improved properties to obtain a residual land price; and an approach that matches vacant lot transactions with subsequent sales of the same properties after they have been developed. We also compare estimated coefficients for land-related variables in a hedonic model that combines vacant land and improved property transactions; there are significant differences in almost all cases.

Our analysis confirms previous findings regarding the difficulty of using hedonic and residual methods for land valuation. Hedonic methods generally fail to satisfy IAAO and other criteria and produce a significant fraction of sometimes large negative land valuations. The latter issue also arises with the residual method. We also find, not surprisingly, that the coefficients for land-related variables in an improved property transaction model generally differ significantly from those in a vacant land sales model.

In contrast, the matching approach yields promising results. Our land leverage estimates display a pattern over time that is consistent with the housing market cycle. They also vary across space in the expected manner, with higher values in central areas. Moreover, this method satisfies the criterion of ease of implementation. Finally, the range of values seems reasonable, although it would be desirable to appraise a sample of properties to check the estimates.

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Appendix

Table A1

Means for land and location characteristics.

Variable	Maricopa County vacant land sales, 2015-2018	Maricopa County improved property sales, 2015-2018	Market 26 vacant land sales, 2015-2018
Land area (sq. ft.)	36,179	9,720	38,133
Distance to CBD (miles)	23.4	17.6	26.3
Flood zone (percentage of property in zone)			
Not in flood zone	95.074	98.952	—
Floodway	0.581	0.028	—
Flood fringe	0.711	0.702	—
Flood plain	3.634	0.318	—
Subdivisible (dummy)	0.104	0.026	0.077
Zoning (dummies)			
Planned development	0.124	0.264	0.101
Townhouse	<0.001	0.005	0.000
Min. lot size 4,000 to 9,000 sq. ft.	0.157	0.586	0.043
Min. lot size 10,000 to 24,000 sq. ft.	0.157	0.089	0.213
Min. lot size 30,000 to 35,000 sq. ft.	0.117	0.014	0.193
Min. lot size one acre	0.425	0.024	0.450
Min. lot size 70,000 to 190,000 sq. ft.	0.011	<0.001	0.000
Other	0.009	0.015	0.000
Submarket (dummies)			
1	0.009	0.064	—
2	0.014	0.076	—
3	0.014	0.035	—
4	0.038	0.048	—
5	0.032	0.046	—
6	0.009	0.045	—
7	0.110	0.033	—
8	0.054	0.022	—
9	0.086	0.077	—
10	0.002	0.050	—
11	0.079	0.018	—
12	0.007	<0.001	—
13	0.003	0.016	—

Variable	Maricopa County vacant land sales, 2015-2018	Maricopa County improved property sales, 2015-2018	Market 26 vacant land sales, 2015-2018
14	0.025	0.001	—
15	0.045	0.057	—
16	0.019	0.040	—
17	0.009	0.055	—
18	0.047	0.021	—
19	0.006	0.014	—
20	0.085	0.018	—
21	<0.001	<0.001	—
22	0.004	0.003	—
23	0.022	0.052	—
24	0.041	0.041	—
25	0.129	0.040	—
26	0.093	0.105	—
27	0.015	0.024	—
Other variables in data set			
Quarterly time dummies	Yes	Yes	Yes
Neighborhood dummies	No	No	Yes
Improvement characteristics	No	Yes	No
N	6,982	288,204	653

Table A2

Vacant land sales regressions, Maricopa County and Market 26, 2015-2018.

Variable	Maricopa County OLS	Market 26 OLS	Market 26 SEM	Market 26 robust M
Intercept	7.591 (0.222)***	2.896 (0.606)***	2.785 (0.658)***	4.788 (0.481)***
Log of land area	0.509 (0.020)***	0.904 (0.054)***	0.907 (0.052)***	0.663 (0.043)***
Distance to CBD	-0.059 (0.002)***	-0.034 (0.011)***	-0.034 (0.016)**	-0.008 (0.009)
Flood zone				
Floodway	-0.008 (0.001)***	—	—	—
Flood fringe	0.004 (0.001)***	—	—	—
Flood plain	-0.005 (0.000)***	—	—	—
Subdivisible	0.067 (0.033)**	-0.250 (0.065)***	-0.290 (0.066)***	-0.058 (0.052)
Zoning				
Planned development	0.923 (0.081)***	1.064 (0.081)***	1.111 (0.083)***	0.729 (0.064)***
Townhouse	1.717 (0.447)***	—	—	—
Min. lot size 4,000 to 9,000 sq. ft.	0.118 (0.082)	1.010 (0.153)***	1.034 (0.145)***	0.519 (0.122)***
Min. lot size 10,000 to 24,000 sq. ft.	0.651 (0.082)***	0.957 (0.061)***	0.855 (0.066)***	0.737 (0.049)***
Min. lot size 30,000 to 35,000 sq. ft.	0.380 (0.084)***	0.520 (0.039)***	0.525 (0.043)***	0.390 (0.031)***
Min. lot size one acre	-0.033 (0.083)	—	—	—
Min. lot size 70,000 to 190,000 sq. ft.	0.246 (0.112)**	—	—	—
Submarket				
2	-0.111 (0.103)	—	—	—
3	-0.261 (0.101)***	—	—	—
4	-1.599 (0.091)***	—	—	—
5	0.561 (0.091)***	—	—	—
6	-0.625 (0.113)***	—	—	—
7	0.156 (0.083)*	—	—	—

Variable	Maricopa County OLS	Market 26 OLS	Market 26 SEM	Market 26 robust M
8	-0.358 (0.087)***	—	—	—
9	-0.906 (0.084)***	—	—	—
10	-0.572 (0.172)***	—	—	—
11	-0.568 (0.087)***	—	—	—
12	-0.810 (0.130)***	—	—	—
13	-0.356 (0.165)**	—	—	—
14	1.165 (0.095)***	—	—	—
15	-0.351 (0.088)***	—	—	—
16	-1.046 (0.098)***	—	—	—
17	-1.308 (0.114)***	—	—	—
18	0.186 (0.091)**	—	—	—
19	0.206 (0.128)	—	—	—
20	0.362 (0.085)***	—	—	—
21	-1.629 (0.267)***	—	—	—
22	-1.855 (0.151)***	—	—	—
23	-0.877 (0.096)***	—	—	—
24	-0.067 (0.088)	—	—	—
25	-0.890 (0.087)***	—	—	—
26	0.289 (0.084)***	—	—	—
27	-0.624 (0.102)***	—	—	—
Neighborhood				
2	—	0.079 (0.224)	0.118 (0.251)	0.035 (0.178)
3	—	-0.315 (0.207)	-0.260 (0.236)	-0.405 (0.164)**
4	—	0.268 (0.173)	0.312 (0.167)*	0.374 (0.137)***

Variable	Maricopa County OLS	Market 26 OLS	Market 26 SEM	Market 26 robust M
5	—	0.357 (0.223)	0.423 (0.259)	0.529 (0.177)***
6	—	0.131 (0.201)	0.038 (0.205)	0.418 (0.160)***
7	—	0.157 (0.177)	0.264 (0.181)	0.263 (0.141)*
8	—	0.210 (0.191)	0.218 (0.200)	0.282 (0.152)*
9	—	-0.075 (0.182)	-0.038 (0.191)	-0.156 (0.144)
12	—	-0.052 (0.183)	0.074 (0.193)	-0.042 (0.145)
13	—	0.078 (0.222)	0.049 (0.259)	0.015 (0.176)
Quarter				
2015Q2	-0.019 (0.043)	-0.135 (0.073)*	-0.105 (0.065)	-0.102 (0.058)*
2015Q3	0.013 (0.046)	-0.081 (0.074)	-0.023 (0.066)	-0.053 (0.059)
2015Q4	0.078 (0.045)*	-0.069 (0.079)	-0.044 (0.070)	-0.004 (0.063)
2016Q1	0.039 (0.043)	0.098 (0.074)	0.106 (0.077)	0.086 (0.059)
2016Q2	0.056 (0.043)	-0.031 (0.075)	0.067 (0.078)	0.063 (0.059)
2016Q3	0.028 (0.044)	0.108 (0.080)	0.114 (0.082)	0.147 (0.064)**
2016Q4	0.044 (0.044)	0.044 (0.078)	0.083 (0.080)	0.055 (0.062)
2017Q1	0.090 (0.041)**	0.115 (0.068)*	0.122 (0.071)*	0.187 (0.054)***
2017Q2	0.122 (0.041)***	0.072 (0.070)	0.110 (0.072)	0.197 (0.056)***
2017Q3	0.079 (0.042)*	0.153 (0.072)**	0.151 (0.075)**	0.225 (0.057)***
2017Q4	0.134 (0.042)***	0.162 (0.076)**	0.201 (0.079)**	0.165 (0.061)***
2018Q1	0.169 (0.041)***	0.263 (0.071)***	0.290 (0.076)***	0.264 (0.056)***
2018Q2	0.214 (0.042)***	0.183 (0.079)**	0.253 (0.083)***	0.207 (0.062)***
2018Q3	0.178 (0.044)***	0.221 (0.076)***	0.292 (0.080)***	0.231 (0.060)***
2018Q4	0.152 (0.045)***	0.325 (0.082)***	0.354 (0.084)***	0.359 (0.065)***
l (spatial error term)	—	—	0.463 (0.044)***	—

Variable	Maricopa County OLS	Market 26 OLS	Market 26 SEM	Market 26 robust M
N	6,982	653	653	653
R-squared	0.732	0.646	—	0.539
Adjusted R-squared	0.730	0.628	—	—
AIC	—	—	344.4	—

Note: These regressions are the basis for the prediction accuracy statistics reported in Table 3. Standard errors in parentheses (). *** indicates significance at the 1 percent level; ** indicates significance at the 5 percent level; * indicates significance at the 10 percent level.

Table A3

Combined vacant land and improved property sales estimation with interaction terms, Maricopa County, 2015-2018.

Variable	Non-interacted terms	Terms interacted with vacant land transaction dummy
Intercept	7.320 (0.018)***	0.271 (0.071)***
Log of land area	0.193 (0.002)***	0.317 (0.006)***
Distance to CBD	-0.009 (0.000)***	-0.050 (0.001)***
Flood zone		
Floodway	-0.001 (0.000)**	-0.008 (0.001)***
Flood fringe	0.001 (0.000)***	0.002 (0.000)***
Flood plain	-0.001 (0.000)***	-0.004 (0.000)***
Subdivisible	-0.026 (0.002)***	0.092 (0.011)***
Zoning		
Planned development	0.098 (0.003)***	0.825 (0.025)***
Townhouse	0.138 (0.006)***	1.579 (0.139)***
Min. lot size 4,000 to 9,000 sq. ft.	0.055 (0.003)***	0.063 (0.026)**
Min. lot size 10,000 to 24,000 sq. ft.	0.115 (0.004)***	0.536 (0.026)***
Min. lot size 30,000 to 35,000 sq. ft.	0.059 (0.005)***	0.321 (0.027)***
Min. lot size one acre	-0.009 (0.005)*	-0.024 (0.026)
Min. lot size 70,000 to 190,000 sq. ft.	0.009 (0.014)	0.237 (0.037)***
Submarket		
2	0.033 (0.002)***	-0.144 (0.032)***
3	-0.087 (0.002)***	-0.175 (0.032)***
4	-0.403 (0.003)***	-1.196 (0.029)***
5	0.290 (0.003)***	0.271 (0.029)***
6	-0.137 (0.002)***	-0.488 (0.035)***
7	0.193 (0.003)***	-0.037 (0.026)

Variable	Non-interacted terms	Terms interacted with vacant land transaction dummy
8	-0.029	-0.329
	(0.003)***	(0.027)***
9	-0.259	-0.647
	(0.002)***	(0.026)***
10	-0.138	-0.434
	(0.002)***	(0.054)***
11	-0.084	-0.483
	(0.003)***	(0.027)***
12	-0.487	-0.324
	(0.054)***	(0.067)***
13	0.033	-0.389
	(0.003)***	(0.051)***
14	0.426	0.740
	(0.012)***	(0.032)***
15	-0.072	-0.279
	(0.002)***	(0.027)***
16	-0.266	-0.780
	(0.003)***	(0.031)***
17	-0.312	-0.997
	(0.003)***	(0.035)***
18	0.199	-0.013
	(0.004)***	(0.029)
19	0.305	-0.099**
	(0.004)***	(0.040)
20	0.203	0.159
	(0.003)***	(0.027)***
21	-0.396	-1.233
	(0.036)***	(0.090)***
22	-0.304	-1.551
	(0.008)***	(0.048)***
23	-0.280	-0.597
	(0.002)***	(0.030)***
24	-0.029	-0.039
	(0.002)***	(0.028)
25	-0.284	-0.605
	(0.003)***	(0.027)***
26	-0.046	0.334
	(0.002)***	(0.026)***
27	0.061	-0.685
	(0.003)***	(0.032)***
Log of floor area	0.436	—
	(0.002)***	
Basement	-0.004	—
	(0.004)	
Bathrooms	0.033	—
	(0.001)***	

Variable	Non-interacted terms	Terms interacted with vacant land transaction dummy
Improvement class		
3	0.136 (0.007)***	—
4	0.232 (0.007)***	—
5	0.400 (0.007)***	—
6	0.487 (0.010)***	—
Age	-0.013 (0.000)***	—
Age squared	<0.001 (0.000)***	—
Carport	0.035 (0.002)***	—
Garage	0.103 (0.002)***	—
Golf cart garage	0.283 (0.007)***	—
RV garage	0.066 (0.006)***	—
Airplane hangar	0.296 (0.058)***	—
Barn	0.032 (0.009)***	—
Storage shed	0.002 (0.002)	—
Pool	0.068 (0.001)***	—
Spa	0.040 (0.004)***	—
Sports court	0.004 (0.012)	—
Tennis court	0.008 (0.021)	—
Quarter		
2015Q2	0.018 (0.002)***	-0.037 (0.014)***
2015Q3	0.029 (0.002)***	-0.015 (0.014)
2015Q4	0.040 (0.002)***	0.038 (0.014)***
2016Q1	0.067 (0.002)***	-0.028 (0.013)**
2016Q2	0.087 (0.002)***	-0.031 (0.014)**
2016Q3	0.095 (0.002)***	-0.068 (0.014)***

Variable	Non-interacted terms	Terms interacted with vacant land transaction dummy
2016Q4	0.108 (0.002)***	-0.064 (0.014)***
2017Q1	0.137 (0.002)***	-0.047 (0.013)***
2017Q2	0.158 (0.002)***	-0.036 (0.013)***
2017Q3	0.167 (0.002)***	-0.088 (0.013)***
2017Q4	0.184 (0.002)***	-0.049 (0.013)***
2018Q1	0.214 (0.002)***	-0.045 (0.013)***
2018Q2	0.237 (0.002)***	-0.023 (0.013)*
2018Q3	0.244 (0.002)***	-0.066 (0.014)***
2018Q4	0.256 (0.002)***	-0.104 (0.014)***
N	295,186	
R-squared	0.852	
Adjusted R-squared	0.852	

Note: Standard errors in parentheses (). *** indicates significance at the 1 percent level; ** indicates significance at the 5 percent level; * indicates significance at the 10 percent level.