Published in "Journal of Real Estate Portfolio Management", 2020, vol. 26, no. 1, pp. 57-73, which should be cited to refer to this work.
DOI: 10.1080/10835547.2020.1833612

The Importance of Micro-Location for Pricing Real Estate Assets:

The Case of Hotels

By

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ABSTRACT

Traditionally, hedonic pricing studies focusing on commercial real estate control for spatial effects with macro-location dummy variables, for example at MSA or submarket level, and predominantly rely on OLS regression. This approach ignores the importance of micro-location characteristics for predicting sales prices. Additionally, spatial dependences in transaction prices and error terms violate OLS assumptions. We propose an alternative approach that replaces macro-location dummy variables with four location area characteristics (LAC) variables, defined as population, median home value, homeownership rate and average land gradient within a polygon of a 20-minute driving distance around each property in our sample. We compare the location dummy and LAC approach using OLS regression, spatial autoregression (SAR) and spatial autoregression with autoregressive errors (SARAR) for a sample of hotels sold between 2015 and 2017. We find models that include LAC variables to have a superior fit to models including MSA dummy variables, irrespective of estimation method. Additionally, the inclusion of LAC variables allows the reduction of spatial lags and errors.

JEL Classifications: *A14 ● G12 ● M31 ● R32*
Keywords: *Commercial Real Estate, Hotels, Asset Pricing, Location, Spatial Dependence*

Background

Traditionally, studies investigating commercial real estate prices employ dummy variables for metropolitan statistical areas (MSA), counties or submarkets to control for spatial effects in market conditions and rents (e.g. Ling, Naranjo and Petrova, 2018; Chinloy, Hardin and Wu, 2013a, b; Wiley, Benefield and Johnson, 2010; Colwell and Munneke, 2006). Alternatively, a few studies include continuous property market variables at the MSA (Beracha, Hardin and Skiba, 2018) or city level (Corgel, Liu and White, 2015) to model transaction prices.

However, Corgel, Liu and White (2015) provide evidence that macro-level market variables have a weak explanatory power for hotel prices. One explanation for this low explanatory power is that macro-location variables such as MSA dummies ignore micro-location specific variations in hotel characteristics within a geographical market. For example, the Miami metropolitan area, which is one of the markets included in Beracha, Hardin and Skiba (2018), covers Miami, Fort Lauderdale and West Palm Beach. Hotels in a particular segment are likely to differ in their desirability to different types of travelers depending on whether they are, for example, on South Beach, Downtown Miami, Miami International Airport, Fort Lauderdale or Boca Raton. This in turn creates micro-location specific variations that affect rental rates and transaction prices as well as contribute to spatial dependences in transaction prices. Besides econometric modelling issues, these spatial interdependences also have implications for commercial real estate investors aiming at efficiently diversifying their portfolios (Hayunga and Pace, 2010).

The purpose of this study is to develop a differentiated approach to capturing location quality effects that impact transaction prices and result in spatial dependences. In particular, we focus on the explanatory power of micro-location level variables for transaction prices. After testing a number of location-specific characteristics and their impact on sales prices, we select population, home value, homeownership rate and the land gradient as a proxy for topography as our location area characteristics (LAC). Using Geographic Information System (GIS), we derive the LAC variables for a polygon of a 20-minute driving distance around each property in our sample, which is analogous to the trade area approach for retail or hotel real estate and in line with Das, Smith and Gallimore (2018). We then include the LAC variables in our hedonic pricing models.

In our empirical investigation, we compare the traditional approach of including MSA-level location dummies with our LAC approach. While we consider our micro-location specific approach relevant to all commercial real estate types, we focus on hotel for the following reasons. First, hotels have minimal lease contract frictions compared to other property types with longer lease terms, which allows us to control for potentially confounding effects resulting from property type-specific lease characteristics. Second, hotel-specific control variables such as operating performance or class/segments are provided in the Smith Travel Research (STR) database. These variables are not as easily available for other property types such as retail or multi-family.

We find that the inclusion of LAC variables improves the explanatory power of all hedonic pricing model specifications including the ordinary least square (OLS), spatial autoregression (SAR) and spatial autoregression with autoregressive errors (SARAR) model. In particular, we find that LAC variables reduce the size and statistical significance of spatial autoregressive and spatial error effects. Thus, we provide evidence for the ability of our LAC variables to reduce spatial dependences to the point that our OLS models with LAC variables have a superior fit, in terms of lower estimation errors, to SAR or SARAR models without LAC variables. Furthermore, we find that models including the four LAC variables individually as opposed to a principal component based on the four variables and principal component analysis (PCA) in line with Malpezzi and Shilling (2000) yield a superior fit.

We contribute to the literature on the pricing of commercial real estate in a number of ways. Compared to residential real estate, factors that influence commercial real estate transaction prices are relatively under-researched (Beracha, Hardin and Skiba, 2018; Corgel, Liu and White, 2015). Similarly, spatial dependences in commercial real estate prices have received less attention in the literature than those in housing markets (Chegut, Eichholtz and Rodrigues, 2015; Nappy-Choulet and Maury, 2009; Tu, Yu and Sun, 2004). We add to the literature by developing an alternative to the traditionally used macro-location dummy approach (e.g. Beracha, Hardin and Skiba, 2018; Ling, Naranjo and Petrova, 2018; Das and Wiley, 2015; Chinloy, Hardin and Wu, 2013a, b; Wiley, Benefield and Johnson, 2010; Colwell and Munneke, 2006). The advantage of our approach is that first, micro-location specific variations within a geographical area (e.g. a census based MSA) and the resulting spatial dependences can be better controlled for. Furthermore, previous studies on commercial real estate pricing have a preference for OLS regression over spatial autoregression (e.g. Beracha, Hardin and Skiba, 2018; Ling, Naranjo and Petrova, 2018; Corgel, Liu and White, 2015; Chinloy, Harding and Wu, 2013a,b; Bokhari and Geltner, 2011; Wiley, Benefield and Johnson, 2010; Corgel, 2007; Colwell and Munneke, 2006) and only few studies account for spatial dependences in commercial real estate prices (e.g. Freybote, Simon and Beitelspacher, 2016; Chegut, Eichholtz and Rodrigues, 2015; Dermisi and McDonald, 2011, 2010). Given the computational intensity of spatial hedonic models, such as SAR and SARAR, and a lack of intuition in interpreting their spatial parametric estimates, LAC variables in combination with OLS regression offer an effective yet simpler solution to developing pricing models for commercial real estate assets.

Second, researchers and industry practitioners that focus on non-MSA markets and/or are without access to property and market-level performance data can employ our approach to price hotels. Third, our approach can be applied to other commercial real estate types such as retail, office or multifamily. Previous studies for hotel, apartment and retail emphasize the importance of market segmentation (Beracha, Hardin and Skiba, 2018; Das, 2015; Hardin and Carr, 2006; Wolverton, Hardin and Cheng, 1999). As a consequence, future studies may either use our LAC variables or derive additional ones in order to, in combination with market segment dummies, explain transaction prices for other commercial real estate types.

Last, our approach allows for more parsimonious models as market dummies are eliminated. Beracha, Hardin and Skiba (2018), for example, include 24 dummies for different MSAs in their model. Hedonic pricing studies for commercial real estate face the challenge that these assets are relatively thinly traded, particularly during deteriorating and down-markets, which results in a relatively smaller sample size compared to residential real estate transactions. On the other hand, hedonic pricing studies require the inclusion of a number of variables capturing physical, performance, locational, segment and macro-economic characteristics. Particularly studies with smaller sample sizes that have to be more sensitive to the number of variables included in the model, degrees of freedom and statistical power can employ our approach to mitigate these issues.

The remainder of this manuscript is structured as follows. Next, we discuss our LAC variables, data and methodology, which is followed by our results and a conclusion.

Location Area Characteristics (LAC) Variables

Location quality has been identified as an important factor for investment and financing decisions of real estate investors. Malpezzi and Shilling (2000) provide evidence for the importance of location quality for institutional investors. The authors find that institutional investors tilt their portfolios towards high quality locations in terms of income and local employment. Liu, Liu and Zhang (2019) show that the quality of assets in terms of tenant quality and location quality, defined as industry diversity in a specific location, influence the financing decisions of real estate investment trusts (REITs).

The majority of studies investigating asset pricing in commercial real estate markets controls for location quality by including binary variables at the MSA or submarket level in their model (Ling, Naranjo and Petrova, 2018; Chinloy, Hardin and Wu, 2013a, b; Wiley, Benefield and Johnson, 2010; Colwell and Munneke, 2006). A few studies consider continuous location-specific variables in their models. Corgel, Liu and White (2015) control for the economic activity by including the daytime employment base within 3 miles around each hotel in their sample. Beracha, Hardin and Skiba (2018) include MSA-level population in their model and land supply elasticity as measure of availability of land for development. Blal and Graf (2013) find that employment and annual disposable income in a county have a significantly positive impact on hotel sales prices. Corgel (2007) includes zip-code level per capita income in the empirical analysis and finds a positive impact on prices. Dermisi and McDonald (2010) find a significantly positive impact of financial employment on the prices of office buildings. Lockwood and Rutherford (1996) include state-level unemployment rates and income in their pricing model for industrial real estate. Topography such as slope has been found to be an important determinant for land values (Brigham, 1965) as are demographic variables such as homeownership rate, household size and the racial diversity of residents (Gedal, 2018).

To derive the LAC variables for our empirical investigation, we assess a number of micro-location specific variables based on these earlier studies. In particular, we focus on population, median home value, home ownership rate, average land gradient (slope), median household income, average household size, ratio of day-time population over total population, ethnic diversity, annual growth rate in household size, unemployment rate, percentage of senior citizens in population, proportion of wild area and number of businesses. We use ESRI's ArcGIS to collect these LAC variables for each hotel included in our sample. In particular, we define a micro-location of a hotel as the area captured by a polygon of a 20-minute driving distance around the hotel, which is an approach that is similar to the trade area approach in retail or hotel real estate (e.g. Das, Smith and Gallimore, 2018). Our use of GIS to derive LAC variables is also in line with previous studies that emphasized the advantages of geospatial software such as GIS for real estate analysis (e.g. Das, Smith and Gallimore, 2018; Clapp and Rodriguez, 1998; Rodriguez, Sirmans and Marks, 1995). ESRI geocodes demographic and socio-economic data aggregated from different public sources such as the US Census and the American Community Survey as well as private sources such as Experian's Consumer View database and the Survey of American Consumers from GfK MRI. Table 1 presents the descriptive statistics for our initial LAC variables while Table 2 presents their pairwise correlations with sales price and each other.

[Insert Table 1 here]

[Insert Table 2 here]

As shown in Table 2, all variables except unemployment (*UNEMP*) and household size (*HHSIZE*) have a significant pair-wise correlation with the log of sales price, our dependent variable. However, the relationships reported in Table 2 are bivariate, and the effect of individual variables on sales price in a multivariable model may differ. Additionally, a number of variables have high pair-wise correlations, such as population and businesses in a micro-location (0.98) or home value and household income (0.81), which introduces the threat of multi-collinearity. We also conduct multiple analyses in which we estimate our models, to be discussed below, using different combinations of LAC variables in order to derive the ones with the highest explanatory power for our sample[2]. As a result of our analyses, we select population (*Ln(POP)),* home value (*Ln(HOMEV)*), homeownership rate (*HOWN*) and land gradient (*SLOPE*) as the LAC variables that capture micro-location characteristics of hotels in our sample most appropriately. We remove all other LAC variables from our empirical analysis, either due to statistical insignificance in a multivariable setting or high collinearity.

Malpezzi and Shilling (2000) capture location quality using a principal component (PCA) based on the highest Eigenvalue for their location-specific variables. In addition to analyzing the explanatory power of our four LAC variables individually, we follow Malpezzi and Shilling (2000) and measure location quality based on a principal component based on the highest Eigenvalue derived from 1) all micro-location specific variables (LAC_{all})and 2) our four LAC variables (LAC_4). The homeownership rate, percentage of senior population, average land gradient and percentage of wild area load negatively onto LAC_{all} while all other variables load positively onto this component. It explains 32% of variance. Homeownership rate and slope load negatively onto LAC4 while population and median home value load positively on it. The component explains 48% of variance.

To compare our LAC approach, we also investigate the predictive value of ESRI tapestry data, which captures micro-location characteristics, for transaction prices. The ESRI database classifies neighborhoods into different segments, which is called tapestry segmentation. These tapestries are based on data about socio-economic characteristics of residents sourced from private sources and characterize an area in terms of, for example, lifestyle, incomes or consumer

[2] The results of these analyses are available upon request.

preferences. For example, residents in the "Top Tier" of the "Affluent Estates" tapestry are summarized as individuals that "earn more than three times the US household income. They have the purchasing power to indulge any choice […] Aside from the obvious expense for the upkeep of their lavish homes, consumers select upscale salons, spas, and fitness centers for their personal well-being and shop at high-end retailers for their personal effects."[3] The majority of hotels included in our sample (228) are in the "Affluent Estate" tapestry.

Analogously to our LAC variables, the ESRI tapestry segmentation allows to control for heterogeneity within metro areas as they are based on in-depth demographic characteristics of smaller geographical areas (micro-locations) within MSAs. To assess the explanatory power of our LAC variables compared to the ESRI tapestry segmentation, we include binary variables for tapestry segments in selected models in our empirical investigation.

Data

We obtain 817 hotel transactions that occurred between 2015 and 2017 in the US from Costar. We exclude transactions for which no sales price or property age information are available or that were non-arm's length transactions as flagged by Costar. Also, to exclude atypical transactions (outliers), we focus on transactions characterized by capitalization rates between 2% and 20%. We furthermore exclude hotels with less than 10 rooms. In addition to sales price for each hotel in our sample, we obtain sale date, number of floors and land acreage information from Costar. We include the quadratic terms of the property height (*FLOORS*) and property age (*AGEATSALE*) in

[3] http://downloads.esri.com/esri_content_doc/dbl/us/tapestry/1A_Top_Tier_TapestryFlier_G79488_2-18.pdf; For more details about ESRI tapestry segments, please visit http://www.esri.com/data/tapestry and http://desktop.arcgis.com/en/arcmap/latest/extensions/business-analyst/tapestry-descriptions.htm.

our model in line with previous studies (Das, Smith and Gallimore, 2018; Corgel, Liu and White, 2015).

Considering that buyers differ in their characteristics, which affects commercial real estate prices (Corgel and DeRoos, 1994) and spatial dependences (Chegut, Eichholtz and Rodrigues, 2015), we also control for the type of buyer. In particular, we include a dummy for individual buyers (*BUYER.IND*), buyers that are limited liability companies (*BUYER.LLC*) and buyers that are REITs or corporations (*BUYER.REIT.CORP*). Other types of buyers serve as the reference group. We manually create these buyer-type variables based on the true buyer identification in Costar.

In a next step, we match our Costar sample with hotel census data from STR. This approach is in line with previous hotel-specific studies (e.g. Beracha, Hardin and Skiba, 2018; Corgel, Liu and White, 2015) and provides detailed information about hotel operations, which have an impact on transaction prices. We extract data from the STR database wherein the hotels are either manually identified using the CoStar names or matched based on geocoded addresses (manually verified). We obtain the following hotel attributes from STR to be included in our model: hotel size, presence of a restaurant, hotel parent company (e.g. Hilton versus Marriott), hotel location type (e.g. resort versus airport) and hotel operations (e.g. chain management versus franchised or independent).

Beracha, Hardin and Skiba (2018) find that the hotel market is highly segmented, which is in line with findings for other property types (Hardin and Carr, 2006; Wolverton, Hardin and Cheng, 1999). In particular, hotel class determines market segments and has high explanatory power for hotel transaction prices. Hotel class ranges from budget, economy, luxury, mid-price to upscale. We include a dummy for each class except for budget, which is the reference group. Considering the correlation of hotel class and income-specific variables such as adjusted daily rates (ADR), as suggested by Beracha, Hardin and Skiba (2018), we do not include income-specific variables in our models as their effects on transaction prices are captured by the hotel class dummies. We also control for regional heterogeneity by including dummies for broad-level regions as defined by the National Council of Real Estate Investment Fiduciaries (NCREIF). In our empirical investigation, we account for temporal effects by including a binary variable for 2017 and 2016 with 2015 being the reference year. To control for seasonality, we introduce binary variables indicating the quarter in which an asset was sold (first quarter being the reference group).

An overview of the descriptive statistics for our sample are provided in Table 3. The mean hotel sales price is $18.8 million, and prices range from $0.23 to $900 million. In our sample, 34% of the hotels were purchased by independent buyers whereas 14% and 6% were purchased by limited liability companies (LLC) or REITs and corporations respectively. Our average hotel has 4.3 acres of land, is 30-years old and has 123 rooms and four floors. The majority of hotels in our sample are in the mid-price segment (31%), followed by economy (24%), budget (23%), upscale (14%) and luxury (9%). Furthermore, the majority of hotels in our sample has a suburban location (0.40), followed by a small metro/town location (0.21) and interstate location (0.12). With regard to the LAC variables, the average population is 398,687, the average home value is $272,049, the average homeownership rate is 58% and the average land gradient 1.8. However, the ranges of LAC variables vary widely suggesting differences between micro-locations of hotels in our sample.

To improve the reader-friendliness, we do not report the descriptive statistics for the following control variables in Table 3. In our sample, 31% of hotels have restaurants and 12% belong to the all-suites category. Transactions in the sample are almost evenly distributed across the four seasons of the year. Most hotel sales occurred in 2016 (50%) followed by 2017 and 2015 (25% each). Most transacted hotels (73%) are franchised by large chains and 4% are also managed by these chains. The hotel names are based on STR records at the time of sale, which reflects its brand affiliation, if any. The representation of parent brands varies between 1% and 15%, while

23% of hotels in our sample are run independently. Hotel transactions are spread across 23 metropolitan statistical areas (MSA) whose representation in our sample varies between 1% and 4%. Additionally, 16% of all transactions were located in "non-MSA" markets and MSAs with less than five observations, which are grouped together as "other MSAs" to avoid over-fitting in the hedonic model, amount to 43%.

[Insert Table 3 here]

Methodology

To compare the LAC approach to the traditional MSA dummy approach, we structure our empirical investigation as follows. First, we estimate the model in Equation 1 using OLS regression in line with the majority of previous studies investigating commercial real estate prices (Beracha, Hardin and Skiba, 2018; Ling, Naranjo and Petrova, 2018; Corgel, Liu and White, 2015; Chinloy, Harding and Wu, 2013a, b; Bokhari and Geltner, 2011; Wiley, Benefield and Johnson, 2010; Corgel, 2007; Colwell and Munneke, 2006).

$$\ln(P) = \alpha + \beta_1 LAC + \beta_2 A + \beta_3 H + \beta_4 T + \beta_5 S + \beta_6 L + \varepsilon \qquad \textbf{(1)}$$

In Equation 1, *P* denotes transaction price. In line with earlier studies (Das, Smith and Gallimore, 2018; Corgel, Liu and White, 2015), we use the natural log of the transaction price as the dependent variable. *LAC* represents either the four individual LAC variables or one of the two principal components capturing location quality (LAC_{all} and LAC_4) respectively. *A* denotes a vector of physical asset attributes such as number of rooms, floors, age and amenities. Hotel age at the time of sale and the number of floors is also introduced in their quadratic transformations based on Das, Smith and Gallimore (2018), Lin, Rosenblatt and Yao (2009), Smith (2004) and Slade (2000). *H* refers to a vector of hotel market specific attributes such as operation type, buyer type, location type and price segment. *T* is a vector of year dummies to control for price trends. *S* is a vector of quarter dummies to control for seasonality. L represents different types of location controls. ε is the error term.

Next, we apply two spatial econometric approaches. Real estate transaction data have been found to suffer from spatial dependences of observations and residuals (e.g. Clauretie and Daneshvary, 2009; Basu and Thibodeau, 1998; Dubin, 1998). These spatial correlations lead to a violation of OLS assumptions (Pace, Barry and Sirmans, 1998) and make OLS estimation less appropriate for hedonic pricing studies. As a consequence, an emerging real estate literature, particularly in residential real estate, has employed spatial autoregressive models instead of the traditional OLS model to price real estate assets (e.g. Cohen, Ioannides and Thanapisitikul, 2016; Zhu, Füss and Rottke, 2013; Osland, 2010; Fik, Ling and Mulligan, 2003; Pace, Barry and Sirmans, 1998). Another advantage of spatial econometric approaches is that they also address endogeneity problems that result from omitted variables and reduce the requirement to collect data for variables to be included in the model (Freybote, Sun and Yang, 2015; Sun, Tu and Yu, 2005).

At the core of spatial autoregressive models is the idea to extract information from spatially close transactions. In particular, a spatial weight matrix W is applied to assign weights to different spatial lags of the dependent variable (spatial autoregression) or the lagged error (spatial error). The underlying argument for W is that beyond the asset characteristics, asset pricing is also endogenously influenced by geographically neighboring assets, although their influence diminishes with distance. Spatial dependence may arise from the variables omitted from the given specification (Corrado and Fingleton, 2012).

For our sample, we develop a $n \times n$ matrix of Euclidean distances between assets using their geographic coordinates, i.e. latitude and longitude. Thus, each observation has (n-1) neighbors. Each distance in the weight matrix is, then, inversed to account for the diminishing influence with distance. Further, we row-standardize the distances by dividing each distance by the sum of all the distances in the row. Thus, the weight matrix is more sensitive to the notion of "nearest neighbors" whose distances may still vary with geographic context. Our spatial lag model, which accounts for interdependences in the dependent variable (transaction prices) is shown in Equation 2.

$$\mathrm{y} = \mathrm{pWy} + \beta_1 A + \beta_2 H + \beta_3 T + \beta_4 S + \beta_5 B + \beta_6 L + \varepsilon \qquad \textbf{(2)}$$

Where y is the dependent variable, ρ is the spatial lag coefficient, W is the spatial weight matrix and ϕ is the error. A statistically significant ρ implies that the price of a subject asset is influenced by the price of neighboring assets. A positive ρ, thus, would imply that if the neighboring asset sells at a high price, it will also ramp up the price of a subject asset.

The spatial autoregression with autoregressive errors (SARAR) specification is an enhancement to SAR (Equation 2) by also accounting for spatial dependences in the error term. As a consequence, we introduce autoregression in the error term. SARAR is further specified as:

$$\varepsilon = \lambda W \varepsilon + \omega \qquad \textbf{(3)}$$

In Equation 3, λ is the spatial error coefficient and ω is the error. A statistically significant, and positive λ implies that mispricing spills over to neighbors. If the neighboring asset was underpriced, the subject asset will also be underpriced.

Results

OLS Hedonic Pricing Models

The results for our model in Equation 1 using OLS regression are shown in Table 4. For brevity, we do not report the results for binary variables with regard to parent companies, operation type, location type, year of sale, quarter of sale, MSA and region as well as tapestry segmentation. Considering that we use the log of sales price as dependent variable, a unit change in the predictors explains percent change in the price. Model 1 represents the baseline model with MSA dummies.

The results for our baseline model are generally in line with hotel valuation practices and previous studies on hotel transaction prices using OLS regression (Beracha, Hardin and Skiba, 2018; Corgel, Liu and White, 2015). In particular, each extra room increases the value by roughly 0.3%. In line with Das, Smith and Gallimore (2018), Slade (2000) and Brennan, Cannaday and Colwell (1984), we find a significant association between the building height (*FLOORS*) and price. In particular, up to 25 floors, each floor increases the value after which prices fall with an increase in number of floors. Such a non-linear relationship is associated with economies of scale, sense of security and visual amenities, which increase up to 25 floors but then start to decrease with further building height. We suspect that this is also related to the segment of the hotel. Luxury hotels tend to have less rooms and floors to preserve the sense of exclusivity. As expected, with increasing age of a hotel asset, the price falls, which amounts 0.5% per year. However, the coefficient for *AGEATSALE* is significant only at the 10% level. The reliance on reserves in hotel management contracts whereby funds are set aside for future renovations may explain this finding. These cash reserves are estimated in relations to the age of the hotel and past investments in the property. The presence of a restaurant in a hotel and an all-suites classification positively impacts the transaction price of a hotel, which is in line with Corgel, Liu and White (2015) and Das, Smith and Gallimore (2018).

We find that institutional buyers (e.g. REITs or corporations) pay an excess price of up to 25% for assets compared to other types of investors. This result is in line with the expectation that commercial real estate investor types differ in their characteristics, which affects asset prices they are able and willing to pay (Corgel and deRoos, 1994). As expected, hotel class plays a significant role in asset pricing. The higher a hotel is classified in terms of segment/class scale, the larger is the impact of segment on transaction price. Compared to budget hotels, the luxury hotel class implies a 136% increase in price followed by upscale (98%), mid-price (59%) and economy (38%). This finding is in line with Beracha, Hardin and Skiba (2018).

The MSA dummies in our model (*results not reported*) are individually and as a group significant in the pricing equation. We do not find a significance association between the operational model (independent, management contract or franchised) of a hotel and its transaction price (*results not reported*). Compared to airport hotels, other localities such as highways, small metro/towns and suburban lead to a discount in sales price. We find neither a significant price trend between 2015 and 2017 nor significant seasonality in hotel prices across the four quarters. With regard to parent company, we find that only two specific brands, which are positioned in the economy-midscale segment, have a significant effect on the selling price. The premium for these two operators is in line with Das, Smith and Gallimore (2018), who argue that after controlling for the factors that a brand stands for, such as size, quality, location type and amenities, the brand name itself is likely to have diluted marginal relationship with transaction price. Overall, our first model using the MSA dummies explains 83% (adjusted R^2) of variation in transaction prices. The adjusted R^2 of our model is noticeably larger than the adjusted R^2s reported in earlier studies with hedonic pricing models (OLS) for hotel (Beracha, Hardin and Skiba, 2018; Corgel, Liu and White, 2015), which were around 80%.

In Model 2, we replace the MSA dummies with binary variables controlling for the ESRI tapestry segment and the region. Our results for Model 2 are generally in line with Model 1, except for significant coefficients on the quadratic term of age (*AGESQ*) and the individual buyer variable (*BUYER.IND*). However, the second model has a higher explanatory power with an adjusted R^2 of 85%. For brevity, we do not report the coefficients of the tapestry segment dummy variables, a majority of which are highly significant. We find that hotels located in Tapestry 3C ("Trendsetters") and 8D ("Downtown Melting Pot") achieve the highest prices, controlling for other factors. Typical "Trendsetters" are 36 years old (median) and earn $63K per annum (median). These trendsetters are financially active, prefer public transportation, travel frequently and eat healthy, for example at Whole Foods and Trader Joe's. Households in the "Downtown Melting Pot (8D)" are 38 years old, ethnically diverse professionals with \$50K income. These "8D" households are predominantly white or Asians, are likely to own cars and use credit card debt. Our results for Model 2 suggest that including characteristics of micro-locations within a metro area, in which properties are located in, allows explaining transaction prices better. However, a shortcoming of the tapestry segmentation approach, compared to our LAC approach, is that it requires the inclusion of 67 tapestry dummies in our model. This renders the tapestry segmentation approach unsuitable for investigations with smaller samples.

In Model 3 in Table 4, we introduce the LAC variables, in particular population, median home value, homeownership rate and the average land gradient or slope. The four LAC variables replace the 67 tapestry segments variables from Model 2. Our results are in line with Model 2, however, the coefficient on land size (*LANDAC*) is significant, which may be a result of removing 67 dummy variables from our model. The coefficients on all LAC variables are significant at the 1% and 5% level respectively. In particular, a one percent increase in the local population (*log(POP)*) increases the value by 0.11%. Population in a micro-location is correlated with economic activity to which commercial real estate prices are sensitive (Corgel, Liu and White, 2015; Blal and Graf, 2013; Dermisi and McDonald, 2010). Furthermore, a one percent increase in the home value (*log(HOMEV))* is associated with a 70% increase in hotel prices in the respective area. While population captures economic activity, home values are expected to capture the quality of a micro-location such as a neighborhood. We also find that homeownership rates (*HOWN*) have a negative association with hotel prices in the respective area. Each percent increase in *HOWN* is associated with 68% decrease in hotel prices. An explanation for our finding may be that areas in which hotels with high income-potential are located, such as the airport or downtown areas, are not residential neighborhoods, but are dominated by other uses such as industrial, multi-family, retail and office. Last, an increase in average slope of the land is associated with a decrease in hotel price. A greater slope hereby proxies for relatively more difficult terrain, which may increase the cost of constructing, maintenance and transportation costs and is likely to affect the attractiveness to visitors and/or the profitability of a hotel asset to investors and developers. Overall, our model including the LAC variables (Model 3) has a slightly higher explanatory power than the model with tapestry segmentation dummies (Model 2) with an adjusted R^2 of 86%. The fact that Model 2 and 3 in Table 4 have the same R^2, but Model 3 has the higher adjusted R^2 emphasizing the advantages of the LAC approach with four variables over the tapestry segmentation approach with 67 variables.

Finally, we present our model with LAC and regional dummies in form of Model 4 in Table 4. Including regional dummies does not increase the explanatory power of the model in terms of adjusted R^2 or change our results with regard to Model 3. However, the coefficient on homeownership rate (*HOWN*) loses significance. Overall, our results in Table 4 suggest that including LAC variables allows to increase the explanatory power for transaction prices not only compared to the traditional model using MSA dummy variables, but also compared to tapestry segmentation dummies. An econometrically important advantage of the LAC model, compared to the tapestry segmentation model, is that it is less costly in terms of degrees of freedom as a large number of tapestry segment dummies is replaced by four continuous variables characterizing a hotel's micro-location. Furthermore, our model is applicable to smaller markets for which MSA designation or Costar submarket definitions do not exist.

[Insert Table 4 here]

Spatial Hedonic Pricing Models

Table 5 presents the results of our spatial autoregressive (SAR) model, which accounts for spatial dependences in transaction prices, are shown in Equation 2. These models control for all the variables included in the baseline model but vary from each other in terms of spatial treatments (location dummy and LAC). For brevity, we focus on the LAC variables and do not report the results for all other variables which are broadly unaltered.

Model 1 in Table 5 does not include any location-specific variables but introduces spatial lags of the dependent variable in the model. Such a model should be effective in capturing location effects due to omitted variables. Model 2 includes the traditional MSA dummies, Model 3 includes regional dummies, but no MSA dummies, while Model 4 includes the LAC variables and Model 5 includes the LAC and regional dummy variables. The results for all LAC variables are robust to different model specifications and consistent with our results for the respective OLS model in Table 4. As spatial autoregressive models are based on maximum likelihood estimators (MLE), they do not report the R^2 of the model. Yet, we can compare OLS and MLE models across the error (MAPE). The lower the MAPE, the better is the fit of a model. Our model with MSA dummies in Table 5 has a superior fit based on a MAPE of 0.0249 than the respective model in Table 4 (0.0256). This provides evidence for the superiority of spatial econometric approaches to modeling real estate prices over the OLS regression approach. Furthermore, our model including LAC and regional dummy variables (Model 5) has a superior fit than any other spatial model in Table 5, albeit the difference in MAPE between the LAC only model (Model 4) and LAC and regional dummy model (Model 5) is very small. As indicated by the significantly positive ρ for all models in Table 5, a positive spatial autocorrelation of prices is present. Therefore, if prices of neighboring properties increase, the price of a subject property is also positively affected, which is expected. Interestingly, including LAC variables in the model reduces the spatial autocorrelation as indicated by a decreasing spatial lag coefficient (ρ) from 0.46 (Model 1) to 0.11 (Model 5). Lastly, Model 5 in Table 5 also has the smallest MAPE compared to the respective OLS model in Table 4, which has a MAPE of 0.0234.

Overall, our results for the SAR models in Table 5 suggest that including the LAC variables reduces spatial dependences in transaction prices and results in a superior fit compared to any other SAR or OLS model. To some extent, our findings support the claim of previous studies that spatial dependences may be a result of omitted variables (Corrado and Fingleton, 2012; Gibbons and Overman, 2012). Further, considering that the model with the LAC and regional dummy variables in Table 4 and 5 have relatively close MAPE, our results suggest that LAC variables may represent an approach to reduce the effects of spatial dependences in commercial real estate prices on OLS-based results. SAR models require a higher degree of computational sophistication and are more difficult to interpret compared to OLS regression results, which can be directly interpreted as a linear equation of asset valuation. Particularly, if omitted variables are the main motivation for including spatial dependences in the modelling of prices (Corrado and Fingleton, 2012), a model including LAC variables in combination with OLS regression should be preferred in hedonic pricing studies for its simplicity and fit.

[Insert Table 5 here]

In addition to the dependence in spatial lags, real estate prices may also be autoregressive in terms of spatial errors. In other words, both the pricing and mispricing may affect spatially close properties. To control for the spatial dependences in errors also, we run the SARAR models which simultaneously introduce spatial lag and spatial error into the hedonic models, as shown in Equation 3. The results are presented in Table 6 and are consistent with the results presented in Table 5. A model with LAC and regional dummy variables (Model 5) is superior to all other models in terms of model fit (MAPE). The significant spatial error coefficient (λ) indicates the presence of spatial dependences in errors. However, from Model 1 to Model 5 in Table 6, the spatial error coefficient decreases and is significant only at the 10% for Model 5, which includes LAC and regional dummy variables. Overall, our results in Table 6 suggest that the introduction of LAC variables reduces spatial effects (ρ and λ) both in terms of magnitude and statistical significance.

[Insert Table 6 here]

Table 7 presents our SARAR results for the location quality factors, LAC_{all} and LAC_4. Both location quality factors have a significantly positive relationship with hotel prices, but the *LAC4* coefficients are larger than the LA_{Call} coefficients. Including regional dummies improves the model fit, based on the reduction in the MAPE. Interestingly, the MAPE metrics for the models in Table 7 are larger than the MAPE for model 6 (0.0231) in Table 6, which included the individual LAC variables and regional dummies. This indicates that the derivation of a principal location quality component using PCA leads to a loss of information to some degree that in turn affects the model fit.

[Insert Table 7 here]

Last, Table 8 presents the results for SARAR models that include the individual LAC variables (LAC column), LAC factors (LAC_{all} and LAC_4 column) and traditional MSA dummy variables to assess the fit of models that combine macro- and micro-location variables. The results for the individual LAC variables are in line with Table 6. Similar to regional dummies (Table 6), including MSA dummies in a model with the individual LAC variables results in an insignificant coefficient on homeownership rate (*HOWN*). Interestingly, combining the LAC variables with the MSA dummies further reduces the MAPE compared to model 5 (LAC only) and 6 (LAC and regional dummies) reported in Table 6. Additionally, the spatial lag and error coefficients for the SARAR model are insignificant, which suggests that combining variables capturing metropolitan area and micro-location characteristics in a model allows to eliminate spatial dependences in dependent variable and errors. While the inclusion of numerous MSA dummies may not be feasible for commercial real estate studies with small sample sizes, our results in Table 8 suggest that a combination of MSA dummy and LAC variables in a model has a superior fit in addition to reducing the effects of spatial dependences.

The results for the location quality components, LA_{Call} and LAC_4, are in line with Table 7. The inclusion of MSA dummies as opposed to regional dummies fails to result in a better fit, in terms of reducing the MAPE. Furthermore, the model with individual LAC and MSA dummies is superior in fit to the models with LAC factors and MSA dummies. This is in line with the findings for Table 5 and 6.

[Insert Table 8 here]

Conclusion

Previous studies investigating the pricing of commercial real estate commonly use a macro-location dummy approach to control for spatial effects and predominantly rely on OLS regression (Beracha, Hardin and Skiba, 2018; Ling, Naranjo and Petrova, 2018; Chinloy, Hardin and Wu, 2013a, b; Wiley, Benefield and Johnson, 2010; Colwell and Munneke, 2006). This approach ignores the importance of micro-location characteristics for the modelling of transaction prices and spatial dependences in transaction prices and errors, which violate OLS assumptions. Additionally, the inclusion of location dummies reduces the degrees of freedom and affects statistical power, particularly for investigations with small sample sizes. Our study investigates an alternative approach that replaces the traditional location dummies with four LAC variables that characterize micro-locations and capture location quality. The LAC variables are population, median home value, homeownership rate and the average slope within a polygon of a 20-minute driving distance around each property in our sample.

In our empirical investigation, we employ OLS regression, spatial autoregression and spatial autoregression with autoregressive errors to hotel transaction data over the period of 2015 to 2017. We find that the LAC approach, particularly in combination with regional or MSA dummies, has a superior fit to the traditional model with MSA dummies, irrespective of the estimation used. Models with the four individual LAC variables also have a superior fit to models that include a principal component capturing location quality based on the four LAC variables, in line with Malpezzi and Shilling (2000). Additionally, we find that including individual LAC variables reduces spatial lags and errors. Our findings suggest that micro-location characteristics not only have explanatory power for transaction prices but their inclusion in a hedonic pricing model is also a suitable approach for investigators that prefer OLS regression but are concerned with spatial dependences. Future studies may use our findings as a starting point to investigate micro-location characteristics and location quality in the context of other property types or the impact of interaction effects of LAC and other variables on transaction prices.

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Table 1: Summary Statistics for LAC Variables

	Mean	Min	Max	Stdev	Obs
Ln(POP)	12.16	3.95	14.61	1.50	817
Ln(HOMEV)	12.35	11.17	13.82	0.55	817
HOWN	0.58	0.21	0.85	0.11	817
SLOPE	1.82	0.00	8.34	1.35	817
Ln(HHINC)	11.25	10.61	12.09	0.26	817
HHSIZE	2.52	1.88	4.23	0.30	817
DTPOP	1.12	0.68	1.97	0.18	817
DIV	56.63	6.50	91.10	20.25	817
HHGROW	0.83	-1.19	3.65	0.63	817
UNEMP	5.40	0.00	12.40	1.84	817
SEN	0.16	0.06	0.49	0.05	817
Ln(BUS)	9.00	2.48	11.97	1.46	817

Note: The following variables denote the local area characteristics within the region defined by 20-minutes driving distance from each asset. Ln() denotes natural logarithms operator. POP is the population;, HOMEV is the median home value; HOWN is the homeownership rate; SLOPE is the average land gradient; HHINC is the average household income; HHSIZE is the average household size; DTPOP is the ratio of day-time population over total population; DIV is the ethnic diversity index (larger values denote higher diversity); HHGROW is the average annual growth rate in household size; UNEMP is the unemployment rate; SEN is the percent of senior citizens in the population and BUS is number of businesses.

Table 2: Pairwise Correlations Across Local Area Characteristics

	PRICE	POP	HOMEV	HOMN	SLOPE	HHINC	HHSIZE	DTPOP	DIV	HH GROW	UN EMP	SEN	BUS
PRICE	1.00												
POP	0.54***	1.00											
HOMEV	0.50***	0.34***	1.00										
HOMN	-0.47***	-0.50***	-0.34***	1.00									
SLOPE	-0.09*	-0.19***	0.18***	0.09*	1.00								
HHINC	0.46***	0.41***	0.81***	-0.07*	-0.06	1.00							
HHSIZE	0.04	0.27***	0.09**	0.10**	-0.07	0.09**	1.00						
DTPOP	0.42***	0.27***	0.24***	-0.59***	-0.07*	0.23***	-0.40***	1.00					
DIV	0.45***	0.65***	0.37***	-0.58***	-0.21***	0.25***	0.49***	0.19***	1.00				
HHGROW	0.26***	0.36***	0.25***	-0.22***	-0.12***	0.29***	0.10**	0.19***	0.33***	1.00			
UNEMP	-0.04	0.16***	-0.34***	-0.13***	-0.16***	-0.41***	0.22***	-0.11**	0.34***	-0.10**	1.00		
SEN	-0.24***	-0.52***	-0.05	0.42***	0.08*	-0.16***	-0.51***	-0.12***	-0.51***	-0.28***	-0.08*	1.00	
BUS	0.58***	0.98***	0.40***	-0.55***	-0.14***	0.47***	0.15***	0.41***	0.61***	0.35***	0.08*	-0.47***	1.00

*Note: The table provides pairwise correlation across local area characteristics surrounding the 817 hotel assets included in the study. Variable definitions are in Table 1. ***,** and * denote statistical significance at 0.1%, 1% and 5% levels respectively.*

Table 3: Descriptive Statistics

	Mean	**Min**	**Max**	**Stdev**
PROPERTY				
PRICE	18,757,209	230,000	900,000,000	49,749,163
ROOMS	122.88	12	2,002	133.01
FLOORS	4.20	1	50	4.52
AGE AT SALE	30.18	1	204	21.23
LANDAC (land acreage)	4.27	0	382	17.72
RESTAURANT	0.31	0	1	
ALL_SUITES	0.12	0	1	
Local Area Characteristics (within 20-minute driving distance)				
POP (Population)	397,687	52	2,215,369	405,645
HOMEV (Median home value)	272,049	71,230	1,000,001	182,369
HOWN (Homeownership rate)	0.58	0.21	0.85	0.11
SLOPE (average land gradient)	1.82	0	8.34	1.35
BUYER				
BUYER.IND (individual buyer)	0.34	0	1	
BUYER.LLC (LLC buyer)	0.14	0	1	
BUYER.REIT.CORP (REIT or corporate buyer)	0.06	0	1	
LOCATION (SEGMENT)				
Airport	0.06	0	1	
Interstate	0.12	0	1	
Resort	0.10	0	1	
Small Metro/Town	0.21	0	1	
Suburban	0.40	0	1	
Urban	0.11	0	1	
CLASS				
Budget	0.23	0	1	
Economy	0.24	0	1	
Luxury	0.09	0	1	
Mid-price	0.31	0	1	
Upscale	0.14	0	1	

Note: This table provides the summary of 817 hotel transactions in the US between 2015 and 2017. Data from three different sources were merged for the analysis (Costar, STR, ESRI).

Table 4: OLS Models

	Baseline	**Region + Tapestry Dummies**	**LAC**	**LAC + Region dummies**
	(1)	**(2)**	**(3)**	**(4)**
(Intercept)	**14.17*****	**14.00*****	**5.15*****	**4.91*****
ROOMS	**0.003*****	**0.003*****	**0.003*****	**0.003*****
FLOORS	**0.10*****	**0.08*****	**0.08*****	**0.08*****
FSQ	**-0.002*****	**-0.001*****	**-0.002*****	**-0.002*****
AGEATSALE	**-0.01***	**-0.01*****	**-0.01*****	**-0.01*****
AGESQ	0.00	**0.0001****	**0.00004****	**0.00004****
LANDAC	0.00	0.00	**0.0001****	**0.0001****
RESTAURANT	**0.22*****	**0.23*****	**0.25*****	**0.24*****
ALL_SUITES	**0.17****	**0.20****	**0.15***	**0.15***
log(POP)			**0.11*****	**0.13*****
log(HOMEV)			**0.70*****	**0.67*****
HOWN			**-0.68****	**-0.42**
SLOPE			**-0.06*****	**-0.07*****
BUYER.IND	-0.06	**-0.10***	**-0.09***	**-0.10***
BUYER.LLC	-0.08	-0.08	-0.05	-0.04
BUYER.REIT.CORP	**0.25****	**0.22****	**0.17***	**0.16***
Economy	**0.38*****	**0.38*****	**0.35*****	**0.36*****
Midprice	**0.59*****	**0.58*****	**0.55*****	**0.55*****
Upscale	**0.98*****	**0.93*****	**0.94*****	**0.94*****
Luxury	**1.36*****	**1.21*****	**1.30*****	**1.32*****
Parent Company dummies	Yes	Yes	Yes	Yes
Operation type dummies	Yes	Yes	Yes	Yes
Location type dummies	Yes	Yes	Yes	Yes
Year of sale dummies	Yes	Yes	Yes	Yes
Quarter of sale dummies	Yes	Yes	Yes	Yes
MSA dummies	Yes	No	No	No
Region dummies	No	Yes	No	Yes
Tapestry segmentation dummies	No	Yes	No	No
R^2	0.84	0.87	0.87	0.87
Adj. R^2	0.83	0.85	0.86	0.86
Num. obs.	817	817	817	817
MAPE	0.0256	0.0235	0.0236	0.0234

*Notes: This table provides the results for the models using OLS regression. The analysis is based on 817 hotel sales in the US between 2015 and 2017. Variable definitions are in Table 1 and 3. MSA is the metropolitan statistical area classification. Region is NCREIF region classification (each region includes multiple states). Tapestry is a micro area demographic profile based on cluster analysis developed by ESRI. MAPE is the mean absolute percent error. ***,** and * denote statistical significance at 0.1%, 1% and 5% levels respectively.*

Table 5: Spatial Lag Models (SAR)

	No Location Dummies	MSA Dummies	Region Dummies	LAC	LAC + Region Dummies
	(1)	(2)	(3)	(4)	(5)
(Intercept)	**7.33*****	**9.86*****	**8.83*****	**3.72*****	**3.87*****
log(POP)				**0.11*****	**0.12*****
log(HOMEV)				**0.62*****	**0.62*****
HOWN				**-0.55***	-0.35
SLOPE				**-0.06*****	**-0.07*****
Other determinants	Yes	Yes	Yes	Yes	Yes
Region dummies	No	No	Yes	No	Yes
MSA dummies	No	Yes	No	No	No
Num. obs.	817	817	817	817	817
Parameters	42	66	49	47	54
MAPE	0.0269	0.0249	0.0258	0.0232	0.0231
AIC (Linear model)	42	66	49	46	53
AIC (Spatial model)	1594.39	1407.28	1479.70	1235.18	1221.46
Log Likelihood	-686.34	-619.54	-651.66	-565.15	-554.65
ρ (Spatial lag coeff.)	0.46***	0.28***	0.36***	0.15***	0.11***

*Notes: This table presents the results for the MLE regressions based on spatial autoregression (SAR) models. The analysis is based on 817 hotel sales in the US between 2015 and 2017. Variable definitions are in Table 1. All models control for other hedonic pricing determinants (see OLS models). Their coefficients are broadly similar and, hence, not shown for brevity. MAPE is the mean absolute percent error. ***, ** and * denote statistical significance at 0.1%, 1% and 5% levels respectively.*

Table 6: SARAR (Spatial Autoregressive with Autoregressive Error) Models

	No Location Dummy	**MSA Dummy**	**Region Dummy**	**LAC**	**Region Dummy + LAC**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
(Intercept)	**10.26*****	**10.72*****	**9.92*****	**3.85*****	**3.88*****
log(POP)				**0.11*****	**0.12*****
log(HOMEV)				**0.62*****	**0.62*****
HOWN				**-0.55***	-0.35
SLOPE				**-0.06*****	**-0.07*****
Other determinants	Yes	Yes	Yes	Yes	Yes
Region dummies	No	No	Yes	Mo	Yes
MSA dummies	No	Yes	No	No	No
Num. obs.	817	817	817	817	817
Parameters	43	67	50	47	54
MAPE	0.0259	0.0247	0.0256	0.0232	0.0231
AIC (Linear model)	1594.39	1407.28	1479.70	1235.18	1221.46
AIC (Spatial model)	1417.51	1367.35	1392.34	1224.06	1217.30
Log Likelihood	-665.76	-616.68	-646.17	-565.03	-554.65
λ (spatial error coeff.)	0.54***	0.23***	0.30***	0.05***	0.001*
ρ (spatial lag coeff.)	0.28***	0.23***	0.29***	0.14***	0.11*

*Notes: This table provides MLE regression coefficients based on spatial autoregression with autoregressive errors (SARAR) models. The analysis is based on 817 hotel sales in the US between 2015 and 2017. Variable definitions are in Table 1. All models control for other hedonic pricing determinants (see OLS models). Their coefficients are broadly similar and, hence, not shown for brevity. MAPE is the mean absolute percent error. ***,** and * denote statistical significance at 0.1%, 1% and 5% levels respectively.*

Table 7: SARAR Models with Location Quality (LAC) Factors and Regional Dummy

	LAC_{all}		**LAC_4**	
	(1)	**(2)**	**(3)**	**(4)**
(Intercept)	**10.33*****	**11.49*****	**12.07*****	**12.44*****
LAC_{all}	**0.16*****	**0.15*****		
LAC_4			**0.28*****	**0.25*****
log(POP)				
log(HOMEV)				
HOWN				
SLOPE				
Other determinants	Yes	Yes	Yes	Yes
Region dummies	**No**	**Yes**	**No**	**Yes**
MSA dummies	**No**	**No**	**No**	**No**
Num. obs.			817	817
Parameters	44	51	44	51
MAPE	0.0248	0.0232	0.0247	0.0244
AIC (Linear model)	1401.8	1347.1	1340.9	1316.5
AIC (Spatial model)	1392.3	1345.1	1308.6	1300.0
Log Likelihood	-628.6	-611.4	-610.3	-599.0
λ (spatial error coeff.)	0.41***	0.25***	0.25***	0.17***
ρ (spatial lag coeff.)	0.30***	0.30***	0.16***	0.14***

Notes: This table provides MLE regression coefficients based on spatial autoregression with autoregressive errors (SARAR) models. The analysis is based on 817 hotel sales in the US between 2015 and 2017. Variable definitions are in Table 1. All models control for other hedonic pricing determinants (see OLS models). Their coefficients are broadly similar and, hence, not shown for brevity. MAPE is the mean absolute percent error.

****,** and * denote statistical significance at 0.1%, 1% and 5% levels respectively.*

Table 8: SARAR Models with Location Quality (LAC) Factors and MSA Dummy

	LAC_{all}	**LAC**	**LAC_4**
(Intercept)	**11.88***	**4.52***	**12.48***
LAC_{all}	**0.14***		
LAC_4			**0.24**
log(POP)	**0.14**	**0.10***	
log(HOMEV)		**0.60***	
HOWN		-0.42	
SLOPE		**-0.05***	
Other determinants	Yes	Yes	Yes
Region dummies	**No**	**No**	**No**
MSA dummies	**Yes**	**Yes**	**Yes**
Num. obs.	817	817	817
Parameters	68	71	68
MAPE	0.0243	0.0226	0.0244
AIC (Linear model)	1326.5	1228.0	1291.9
AIC (Spatial model)	1317.5	1226.3	1288.2
Log Likelihood	-590.8	-542.2	-576.1
ρ (spatial lag coefficient)	0.13**	0.11	0.117*
λ (spatial error coeff.)	0.12**	-0.10	0.046*

Notes: This table provides MLE regression coefficients based on the SARA) models. The analysis is based on 817 hotel sales in the US between 2015 and 2017. Variable definitions are in Table 1. All models control for other hedonic pricing determinants (see OLS models). Their coefficients are broadly similar and, hence, not shown for brevity. MAPE is the mean absolute percent error.
****, ** and * denote statistical significance at 0.1%, 1% and 5% levels respectively.*