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Which Way is Up? Orientation and Residential Property Values

Authors Alyson Ma and Andrew Narwold

Abstract Builders have long been cognizant of the importance of the siting of a house on a lot, whether to shelter from prevailing weather, allow better access to natural light, gain a scenic view, or more recently for optimal capture of solar energy. Using 2016–2017 sales data for the County of San Diego, we examine the market valuation of house orientation. San Diego provides a good research area as the topography does not lend itself to a grid-like pattern for the street system. Orientation is divided into eight directions (south, southeast, east, . . .) and hedonic price equations are estimated. In addition, the analysis includes proximity to a cul-de-sac and street intersection as explanatory variables. The results suggest that house orientation is a significant factor in determining house valuation. Houses oriented directly on an east-west axis command a premium over houses oriented on a north-south axis. After correcting for spatial autocorrelation, neither cul-de-sac nor intersection locations are significant factors in determining housing prices. Moreover, a robustness check using a small sample of 241 transactions provides inclusive results regarding a premium for solar panel installation.

Keywords orientation, solar, hedonic, spatial autocorrelation, cul-de-sac, intersection

Location is everything in real estate as given by the mantra of ‘‘location, location, location’’ often repeated by realtors. Location affects values through neighborhood externalities, whether positive such as public services (Sah, Conroy, and Narwold, 2016) or negative from noise pollution or strip clubs (Taggert, Humphreys, and Nowak, 2018). The proximity to a variety of amenities or disamenities (Song and Knaap, 2003) is also dependent on location.

While significant, location and property characteristics combined are insufficient to tease out nuisance differences reflected in the values of similar homes within the same neighborhood. The differences in the values of two nearly identical homes that are across the street from one another may be captured by the orientation of the houses. According to Schmidt (2008), south-facing windows flood the interior living spaces of a home with natural lighting. Site orientation also impacts the monthly utility bills by keeping homes cool in the summers and warm in the winters (Schmidt, 2008).

To our knowledge, there is a lack of research on the orientation of a home as a determinant of price. Our research would be the first to examine whether the

direction the home faces has an impact on the home price. San Diego ranks second in solar installation in California.[1] As developers consider the layout of new projects or homeowners contemplate the decision to install solar panels, the orientation of the home is an important factor to achieve efficient energy input. In addition to the flow of sunlight, site orientation also affects the breeze in the living spaces, as well as the installations of exterior amenities such as satellite dishes.

Studies focus on the neighborhood including urbanization, access to a greenbelt, distance to coast or water, golf course, and open spaces, as well as the quality of the schools while controlling for housing characteristics (Li and Brown, 1980; Pogodzinski and Sass, 1991; Do and Grudnitski, 1995; Grudnitski and Do, 1997; Benson, Hansen, Schwartz, and Smersh, 1998; Irwin, 2002; Asabere and Huffman, 2009; Conway et al., 2010; Laposa and Muller, 2010; Conroy and Milosch, 2011; Gibbons, Mourato, and Resende, 2014; Mittal and Byahut, 2016). There are studies examining the benefits of locating in a cul-de-sac (Asabere, 1990; Song and Knaap, 2003; Matthews and Turnbull, 2007; Asabere and Huffman, 2009), the discount of traffic externalities (Hughes and Sirmans, 1992), socioeconomic characteristics and demographics (Dubin and Sung, 1990; Song and Knaap, 2003), land use policies (Wolch and Gabriel, 1981), and historical architecture (Asabere, Hachey, and Grubaugh, 1989; Narwold, 2008). Moreover, few studies correct for spatial autocorrelation, which could lead to biased estimated results (Cliff and Ord, 1973; Anselin 1988; Can, 1992; Dubin, 1992, 1998). Understanding whether the orientation of the home may have an impact on home prices provides more accurate information of similar homes located in the same neighborhood.

Sah, Conroy, and Narwold (2016) note the geospatial features of San Diego County are unique due to the notably visible canyons, coastline, and open spaces. Similar to Conway et al. (2010), we account for locational externalities with proximity measures and spatial autocorrelation with a spatial lag in a hedonic estimation. Using housing data from San Diego, we determine the value of home orientation using a geographic information system (GIS) with the inclusion of spatial analysis in a hedonic pricing model.

In the next section, we provide a brief review of the literature on home orientation and spatial autocorrelation. We then present the empirical framework and the data. We then discuss the estimation results and close with concluding remarks.

Conceptual Framework

Home Orientation

The direction in which a house faces is of important considerations for buyers in Guangzhou, China (Tan, 2012). According to Tan (2012), south-facing homes are preferred because these properties are not hit by direct sunlight in the afternoon. In a survey of 265 first-time buyers in Greater Kuala Lumpur, Indonesia, Tan (1992) explicitly captures whether the house direction was a main consideration in the home-purchasing decision. His results suggest a lack of evidence to indicate

that the orientation of the home raised the likelihood of homeownership, once attributes such as neighborhood (e.g., crime, pollution), locational (e.g., retail, school, workplace, recreation, transport), structural (e.g., bedroom, bathroom, kitchen), and demographics are taken into consideration.

Aside from sunlight, the orientation of a house may affect the home value for buyers considering solar panels. Studies indicate that the best orientation for solar collectors is due south (Hestnes, 1999; Gunerhan and Hepbasli, 2007). Moreover, Dastrup, Zivin, Costa, and Kahn (2012) find evidence of a solar price premium using San Diego sales records occurring between January 1997 and September 2009. More specifically, solar panels add 3.3% to the sales price of a home after controlling for property characteristics such as home square footage, the number of bedrooms and bathrooms, whether the home has a pool or view, the age of the home, and housing market trends. Hoen et al. (2015) also find that homebuyers are willing to pay a premium for homes with solar photovoltaic systems, in their analysis of eight states (California, Connecticut, Florida, Massachusetts, Maryland, North Carolina, New York, and Pennsylvania) from 2002 to 2013.

According to some estimates (Barbose and Darghouth, 2018), the installation cost of rooftop solar panels per watt generated has decreased by 50% over the past eight years. Increasing awareness of the issues associated with greenhouse gas emissions has also spurred recent investment in rooftop solar systems not only in San Diego but nationally. The combination of an increase in the demand for sustainability (or energy efficiency) and the potential that home orientation allows for more efficient solar capacity leads to the following hypotheses:

$H_{1.1}$: A home with a solar panel installation will have a higher price.

$H_{1.2}$: All orientations with a solar panel installation would have a lower price, relative to south.

Likewise, the more flexibility a builder or homeowner has in laying out a development, the more likely it is that orientation is taken into account in the construction of the home. This could be reflected in one of two ways. In recently developed master-planned communities, streets may be laid out to facilitate the optimal location for solar generation or directional preferences. The second possibility would be that builders of custom homes on larger lots have more discretion over orientation and may site accordingly. The first consideration is captured in H1.2, whereas the second is provided as follows:

H_2: Orientation will be a factor for newer and higher priced homes that are built on lots of at least half an acre.

Intersections and Corner Lots

Diaz and Wolverton (1998) examine the value of locating in an intersection within the neighborhood, which often means the home is on a corner lot. The attractive features of a corner lot include a potentially larger lot, as well as the choice to determine the direction in which the home faces given the two adjacent streets. Asabere and Huffman (2009) estimate approximately 10,000 home sales from

April 2001 to March 2002 in San Antonio, Texas with corner lots as one of their control variables. They find a lack of statistical support to suggest that corner lots affect the prices of homes.

Spatial Autocorrelation

According to Basu and Thibodeau (1998), homes in the same neighborhood share common location amenities, leading to spatial autocorrelation in house prices. They include a spherical autocorrelation function in their semi-log hedonic estimation of single-family properties in Dallas, Texas. Using data on 5,000 transactions between the fourth quarter of 1991 and the first quarter of 1993, the authors find mixed spatially autocorrelated residuals across eight submarkets.

Can (1992) uses the Lagrange multiplier and Moran's I statistics to test for the presence of residual spatial autocorrelation. The estimation consists of hedonic house price specifications of 577 transactions of single-family homes in Columbus, Ohio, in 1980. The author reports that traditional hedonic price specifications omit spatially lagged dependent variables and finds evidence of spatial autocorrelation in the estimated residuals. Moreover, she suggests that the results from models addressing spatial dependence more accurately reflect the workings of the residential real estate markets. Allen, Austin, and Swaleheen (2015) show the importance of correcting for spatial autocorrelation in estimating the effect of highways on housing prices.

Dubin, Pace, and Thibodeau (1999) explain that spatial techniques could improve the accuracy of market value estimates with a parsimonious specification. In particular, rather than including a plethora of regressors, the use of spatial autoregression model specifications allows for fewer explanatory variables to correct for spatial error dependence. In addition to providing more efficient estimates, the spatial statistical technique could assign greater importance to nearby properties as a function of proximity.

Methodology

Hedonic Estimation

We broadly categorize characteristics that determine the market value of a home. For single-family homes, the factors are the property characteristics, neighborhood externalities, and proximity to amenities. The general specification for the hedonic house price equation in semi-log form is given by the following:

$$lnP_i = \alpha_i + \Sigma_{j=1}^{J}\beta_j Prop_{ij} + \Sigma_{k=1}^{k}\beta_k Neigh_{ik} + \Sigma_{m=1}^{M}\beta_m Prox_{im} + \Sigma_{n=1}^{N}\beta_n Orient_{in} + \beta_i Inter_i + \Sigma_{q=1}^{Q}\theta_q + \varepsilon_i, \quad (1)$$

where lnP_i is the natural log of price for observation i. $Prop_{ij}$ captures the characteristics of the property such as the number of bedrooms and bathrooms

and square footage of the living space. Neighborhood externalities, $Neigh_{ik}$, include access to high-quality schools and other municipal services as well as views. Proximity to amenities, $Prox_{im}$, determines whether locational distance to open spaces, coast, or downtown are inversely related to prices. Market trends are captured by the quarterly fixed effects, θ_q.

Spatial Model

Similar to Can (1992), we determine the existence of spatial autocorrelation with Moran's I using Stata 15. To correct for any potential omitted variables due to the spatial dependence, in equation (2) we specify the sales price of a home, P_i, as a function of a spatially lagged dependent variable and a matrix of the independent variables:

$$P_i = f(WP_i, X_i), \tag{2}$$

where W is the spatial weighting matrix. The expression in matrix form is:

$$P_i = \rho WY + X\beta + \varepsilon, \tag{3}$$

where ρ is the spatial lag parameter. The spatial lag, ρWY, captures omitted variables, such as comparable sales of nearby houses in the assessment of a property's value (Can, 1990; Conway et al., 2010).

The inverse-distance spatial-weighting matrix, W, is composed of weights that are inversely related to the distances between the properties. The distances between the homes are computed from the latitudes and longitudes of parcel centroids. The spatial weighting matrix is row-standardized.

Distances and Orientation

ArcGIS is used to develop the various distances identified in this analysis. The distances are measured in feet to the closest feature. For instance, the distance to the ocean measures the linear distance from the centroid of the parcel to the closest point of the ocean. Similarly, distances to downtown, open space, and others follow the same approach. ArcGIS also identifies the angle from the parcel to the nearest street. We assume that houses are oriented toward the closest street in determining the angle of the home orientation. We then categorize this angle into one of eight directions. Setting due north to be zero degrees, we categorize any house that is oriented between 337.5 degrees and 22.5 degrees to have an orientation of north. We use south as the reference orientation and use seven dummy variables for the remaining orientations.

Each parcel is also evaluated as to whether it is closer to an intersection or a cul-de-sac or street end. Those houses that are closer to a cul-de-sac or street end are

Exhibit 1 | Percentage of Parcels by Orientation: A Comparison of Washtenaw and San Diego Counties

	South	East	North	West	NE	NW	SE	SW
Washtenaw	0.177	0.208	0.175	0.200	0.062	0.058	0.058	0.060
San Diego	0.149	0.175	0.154	0.183	0.081	0.087	0.084	0.087

identified with a dummy variable. The expectation here is that houses close to a street end or cul-de-sac face less traffic and noise and would be valued more. Houses that are located at an intersection are also separately identified. When houses are built on corners, the builder often has the choice of two ways to orient the house, and should therefore situate the house to maximize its value. In addition, the market may place a premium on the lack of neighbors (or open space) on one side of the house. We expect houses at intersections to be valued higher than non-intersection houses.

Data

San Diego County provides an ideal setting for exploring the effects of house orientation on housing values. The topography of San Diego includes a large number of canyons and mesas (i.e., plains), which leads to a road network that follows the contours of the land rather than a strict grid framework. The orientation of houses in San Diego is much more diverse than in more traditional cities that have developed along a grid framework. In a city that has streets laid out in a strictly grid system oriented north/south with equal-sized blocks, one quarter of the homes would be expected to be oriented in each of the four cardinal directions. There will be more heterogeneity in house orientation the less grid-like the street layout. By way of comparison, in Exhibit 1 we compare the orientation of houses sold in San Diego County with the orientation of parcels within Washtenaw County (Ann Arbor area), Michigan. Approximately 76% of the parcels in Washtenaw County are oriented in one of the four cardinal directions, reflecting the underlying grid nature of the road system. By contrast, a higher percentage of homes in San Diego County face either Northeast, Northwest, Southeast, or Southwest.

The data for this analysis come from CoreLogic and represents sales in the County of San Diego, California in 2016–2017. Approximately 90,000 parcels traded hands over this two-year period. After filtering for sales of single-family detached housing and transactions that are at arms-length, approximately 27,000 observations remained. Exhibit 2 presents the descriptive statistics for the full data set, while Exhibit 3 provides the mean by orientation. In general, Exhibit 3 shows that the price and characteristics of the homes, on average, are similar irrespective of orientation.

Exhibit 2 | Descriptive Statistics of the Data Set (n = 26,749)

Variable	Mean	Std. Dev.	Min.	Max.
Sale Amount	$750,588	$595,252	$200,000	$7,000,000
Lot Size (ft^2)	17,067	28,488	2,500	298,822
Age	51.4	18.7	1	114
Living Area (ft^2)	1,933	1,109	500	21,392
Baths	2.34	1.11	1	14
Beds	3.45	1.11	0	14
Pool	0.195	0.396	0	1
Cul-de-sac	0.253	0.435	0	1
Intersection	0.103	0.303	0	1
Distance to Ocean	37,977	31,996	67	294,787
Distance to Downtown	77,986	54,899	1,461	319,779
Distance to Open Space	16,309	26,728	12	223,860
Distance to Freeway	7,218	11,587	74	171,154
Distance to Park	2,728	3,324	0	62,948
Distance to Elementary	3,184	3,243	146	59,987
CAASPP Score	2,436	45	2,288	2,555
South	0.150	0.357	0	1
East	0.175	0.380	0	1
North	0.154	0.361	0	1
West	0.183	0.387	0	1
Northeast	0.081	0.273	0	1
Northwest	0.087	0.282	0	1
Southeast	0.084	0.277	0	1
Southwest	0.086	0.281	0	1

The structural characteristics of the house are self-explanatory. All of the distances are reported in feet. *Cul-de-sac* is a dummy variable equal to one if the house is closer to a cul-de-sac or street-end than a street intersection. *Intersection* is a dummy variable equal to one if the distance to the nearest intersection of two or more streets is less than 30 feet. This does not necessarily capture the effect of the house being located on a corner, as it could be a house at a "T" intersection at the top of the "T." Exhibit 4 is a map illustrating these issues.

The CAASPP score is the mean California Assessment for Student Performance and Progress test score for the third grade at the closest public elementary school. This variable should capture the effect of school quality on housing values. It is interesting to note that if houses were being built with no regard to orientation,

Exhibit 3 | Mean of the Data Set by Orientation

	North	South	East	West	Southeast	Northeast	Southwest	Northwest
Sale Amount	725,179	744,532	736,019	720,155	768,655	795,169	786,178	805,217
Lot Size (ft^2)	17,684	17,536	16,280	15,241	17,489	17,559	16,944	19,854
Age	51	51	53	54	48	49	51	49
Living Area (ft^2)	1,893	1,942	1,885	1,844	2,012	2,012	1,978	2,079
Baths	2	2	2	2	2	2	2	2
Beds	3	3	3	3	3	3	3	3
Pool	0	0	0	0	0	0	0	0
Cul-de-sac	0	0	0	0	0	0	0	0
Intersection	0	0	0	0	0	0	0	0
Distance to Ocean	37,887	37,217	36,649	35,683	41,470	39,686	38,714	41,275
Distance to Downtown	74,940	75,813	73,356	71,978	85,911	87,588	85,367	85,205
Distance to Open Space	15,416	15,894	15,965	15,109	17,362	18,409	18,044	17,138
Distance to Freeway	7,616	7,303	6,552	6,592	7,643	7,645	7,698	7,744
Distance to Park	2,751	2,687	2,630	2,578	2,737	2,934	2,847	2,949
Distance to Elementary	3,134	3,188	3,017	3,015	3,303	3,525	3,313	3,396
CAASPP Score	2,434	2,435	2,433	2,432	2,439	2,440	2,440	2,440
Observations	1,893	1,942	1,885	1,844	2,012	2,012	1,978	2,079

Exhibit 4 | Sample Map of Houses Sold

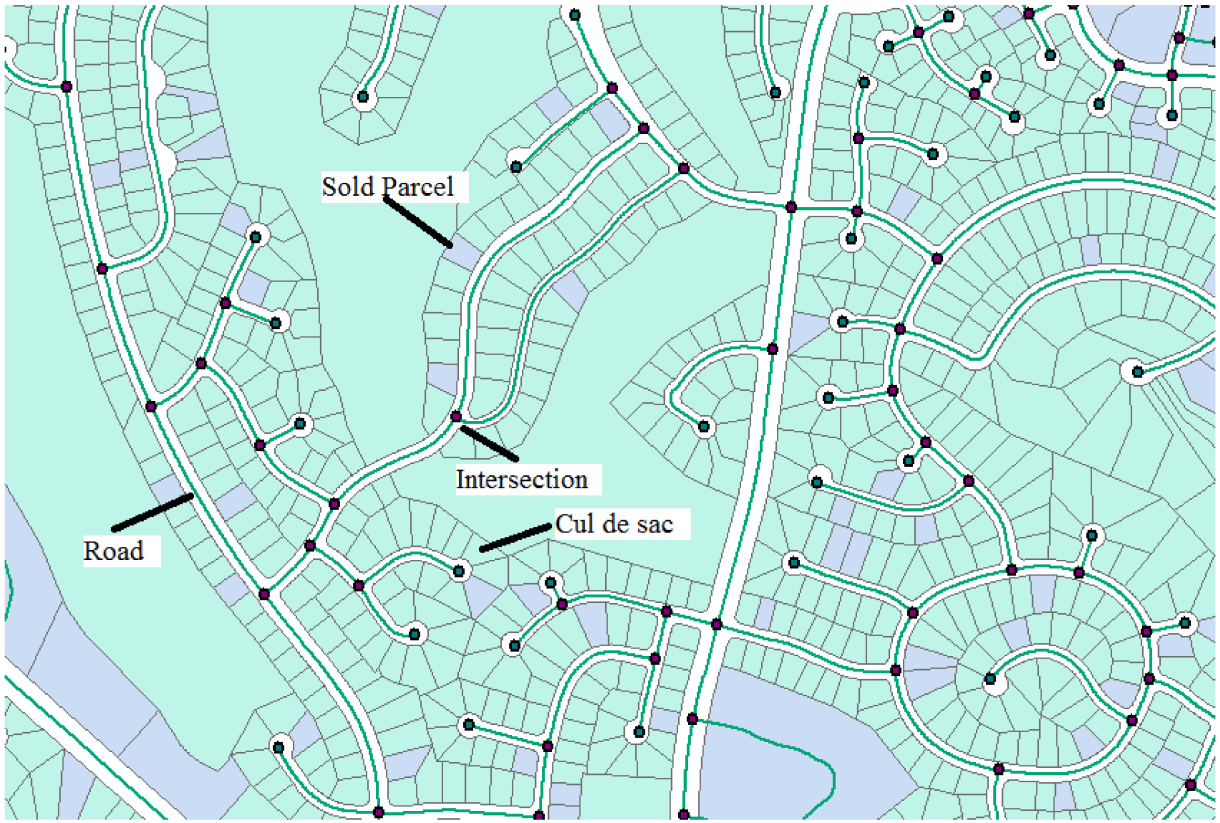

Exhibit 5 | Orientation and Age of the House

	South	East	North	West	NE	NW	SE	SW
Age ≤ 20	0.164	0.154	0.166	0.146	0.089	0.102	0.083	0.096
Age > 20	0.149	0.177	0.153	0.185	0.081	0.086	0.084	0.086

we would expect that approximately 1/8 or about 12.5% of the houses to be oriented to each 45 degrees of the compass. However, in this sample, the four cardinal directions account for about 66% of the houses. This provides some evidence that historically builders considered orientation when siting houses. As evidenced by Exhibit 5, there does not appear to be much of a change in orientation between relatively recently built houses and the majority of the housing stock.

Approximately 10% of the identified transactions during this two-year time period represent a repeat sale of the same property. When correcting for spatial autocorrelation, each observation needs to have its own unique longitude and latitude. For those parcels that changed hands more than once over the sample period, we chose to use the most recent sales information. As this may create an unforeseen bias, we also present estimations of the model using the subset of data without the repeat sales parcels as a robustness check.

Results

Benchmark Estimations

The standard hedonic analysis is conducted using ordinary least squares (OLS) estimation with the natural log of the selling price as the dependent variable. Exhibit 6 presents the results of this estimation. The OLS results for the housing characteristics and distances are for the most part consistent with previous studies and expectations. Some of the distance variables are significant but have the opposite sign from expectations (distance to downtown, distance to park). Similar to Thorsnes (2002), the coefficient on the *Cul-de-sac* variable is insignificant. One reason could be due to the uniqueness of the topography in San Diego. With the canyon landscape, approximately one-quarter of the sample houses are classified as being on a cul-de-sac. This means that a home is more likely to be closer to a cul-de-sac or street end than the next closest intersection. The coefficient on the *Intersection* variable is positive and significant.

Of the seven directional variables (the reference direction being due south), houses oriented to the east or west command about the same premium over houses oriented to the south. East- or west-oriented homes partially face the sun either early in the morning or later in the evening. By comparison, south-facing homes endure the heat from the sun throughout most of the day. Since the majority of

Exhibit 6 | Estimation Results: Sample with Repeat Sales (n = 26,749)

	OLS		2SGLS	
Variables	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.
Log of Lot Size	0.025***	9.43	0.022***	9.22
Age	−0.005***	−14.30	−0.002***	−5.61
Age squared	0.000***	23.07	0.000***	11.52
Log of Living Area	0.560***	81.46	0.475***	79.49
Baths	0.087***	33.49	0.073***	32.82
Bedrooms	−0.039***	−19.80	−0.024***	−14.37
Pool	0.086***	20.96	0.081***	22.91
Cul-de-sac	0.004	1.05	−0.000	−0.04
Intersection	0.010**	0.05	0.005	0.19
Log Dist to Coast	−0.179***	−105.03	−0.078***	−40.86
Log Dist Downtown	0.072***	20.28	−0.050***	−15.14
Log Dist Open Space	−0.033***	−27.49	−0.003**	−2.02
Log Dist Freeway	0.012***	7.88	0.002*	1.62
Log Dist Park	0.004**	2.84	−0.006**	−3.11
Log Dist Elementary	0.034***	13.18	0.013***	5.98
Log CAASPP	6.170***	61.76	2.867***	30.83
East	0.013**	2.76	0.011**	3.02
North	−0.003	−0.73	−0.001	−0.20
West	0.017***	3.11	0.013**	2.92
Northeast	0.010	1.55	−0.001	−0.03
Northwest	0.012**	1.97	0.013**	2.60
Southeast	0.007	1.06	0.008	1.44
Southwest	0.004	0.39	−0.005	−0.81
Constant	−38.375***	−50.00	−16.954***	−46.61
rho			1.456***	0.16
Quarter FE	Yes		Yes	
R^2 / Pseudo R^2	0.783		0.789	
Root MSE	0.237			

Note:
*$p < 0.1$
**$p < 0.05$
***$p < 0.01$

the homes in San Diego lack air-conditioning, the premium for homes oriented to the east or west could be driven by the preferences for cooler home interiors. Moreover, the prevalent of canyon topographies in San Diego provides west-facing homes potential ocean views from the front of the property and east-facing homes from the back of the property.

For the orientations other than the four cardinal directions, only the northwest orientation is significant, increasing home values by about 1.2%. Northwest-facing homes potentially benefit from ocean views with minimal heat from the afternoon sun. Homeowners in homes oriented toward the northwest enjoy natural lighting from most of the afternoon sun.

Exhibit 6 also provides the estimation results from the two-stage generalized least squares approach, which corrects for spatial autocorrelation. For the most part, the results are consistent with those from the OLS estimation. The *Intersection* variable becomes insignificant, and the coefficients on the distance variables are more consistent with theory and previous studies. Namely, the coefficients on both *Distance to Downtown* and *Distance to Park* are now negative and significant as expected, suggesting that homes located further from the downtown or a park are discounted. The correction for spatial autocorrelation shows that simple OLS estimation of hedonic pricing models in real estate can lead to biased results.

Exhibit 7 presents the estimation results for the data after removing those houses that were associated with repeat sales over the two-year time frame. The exclusion of the repeat sales reduced the sample size by about 2,400 homes, leaving us with 24,391 observations. The results are robust to the exclusion of the repeat sales with nearly identical magnitudes and significance.

Hypotheses Testing with Subsamples

While the benchmark estimations provide initial evidence of a premium for home orientation, the range of home prices in the data set is wide with a minimum of $200,000 and a maximum of $7,000,000. We check the robustness of our results by re-estimating the subsamples by price ranges. Exhibit 8 provides the 2SGLS orientation results for the samples without repeat sales. In column (1), we reproduce the results in Exhibit 7 for convenience, while columns (3) and (5) present the findings for the price range of $570,000–$750,000 (between the second and third quartiles) and less than $575,000, respectively. The results in Exhibit 8 indicate that the various orientations are statistically insignificant at the lower home prices, which include track or older homes.

Given our results in Exhibit 8, as a robustness test, we estimate a subsample of newer and higher priced homes on larger lots to test hypotheses 1 and 2. The motivation is that newer and higher priced homes built on lots that are at least half an acre provide the builder or homeowner the choice to decide on the orientation of the home. For example, Exhibit 9 shows a home that could be oriented in different angles given the size, layout, and topography of the lot. However, the home faces a southeast direction.

Exhibit 7 | Estimation Results: Sample without Repeat Sales (n = 24,391)

	OLS		2SGLS	
Variables	Coeff.	*t*-Stat.	Coeff.	*t*-Stat.
Log of Lot Size	0.025***	9.43	0.021***	9.22
Age	−0.005***	−14.30	−0.002***	−5.61
Age squared	0.000***	23.07	0.000***	11.52
Log of Living Area	0.568***	81.46	0.482***	79.49
Baths	0.088***	33.49	0.074***	32.82
Bedrooms	−0.041***	−19.80	−0.026***	−14.37
Pool	0.087***	20.96	0.082***	22.91
Cul-de-sac	0.004	1.05	−0.000	−0.04
Intersection	0.010**	1.96	0.006	1.30
Log Dist to Coast	−0.181***	−105.03	−0.078***	−40.86
Log Dist Downtown	0.073***	20.28	−0.052***	−15.14
Log Dist Open Space	−0.033***	−27.49	−0.002**	−2.02
Log Dist Freeway	0.013***	7.88	0.002	1.62
Log Dist Park	0.006**	2.84	−0.005**	−3.11
Log Dist Elementary	0.034***	13.18	0.013***	5.98
Log CAASPP	6.194***	61.76	2.904***	30.83
East	0.015**	2.76	0.014**	3.02
North	−0.004	−0.73	−0.001	−0.20
West	0.017***	3.11	0.013**	−0.03
Northeast	0.010	1.55	−0.000	2.60
Northwest	0.013**	1.97	0.014**	1.44
Southeast	0.007	1.06	0.008	−0.81
Southwest	0.003	0.39	−0.005	4.05
Constant	−38.621***	−50.00	−31.177***	−46.61
rho			1.439***	86.33
Quarter FE	Yes		Yes	
R^2 / Pseudo R^2	0.790		0.798	
Root MSE	0.237			

Note:
*$p < 0.1$
**$p < 0.05$
***$p < 0.01$

Exhibit 8 | 2SGLS Estimation Results: Sample without Repeat Sales by Home Prices

	Full Sample		$570,000–$750,000		<$575,000	
Variables	Coeff.	*z*-Stat.	Coeff.	*z*-Stat.	Coeff.	*z*-Stat.
East	0.014**	2.76	−0.003	−0.92	−0.005	−1.20
North	−0.001	−0.73	−0.006	−1.66	−0.002	−0.38
West	0.013**	3.11	−0.000	−0.03	0.002	0.45
Northeast	−0.000	1.55	0.001	0.26	−0.000	−0.01
Northwest	0.014**	1.97	0.003	0.77	0.008	1.49
Southeast	0.008	1.06	0.007	1.81	0.002	0.34
Southwest	−0.005	0.39	0.001	0.30	−0.004	−0.68
Pseudo R^2	0.798		0.001		−0.001	

Note: The number of observations in the full sample is 24,391; in the $570,000–$750,000 sample, it is 5,399; and in the <$575,000 sample, it is 12,085.

With the subsample of 241 observations, we determine the orientation and whether the home has a view or solar installation using Google Maps. The views are separated in those overlooking water or green landscape such as golf courses or parks. Moreover, we include a proxy for the number of days a home is on the market (DOM) with the median monthly DOM by ZIP Code, due to a lack of data. Furthermore, we capture the geographical proximities of a home to the green view with an interaction between green view and distance to park and open spaces. Lastly, to test H1.1 and H1.2, we include solar and an interaction between solar and the orientation of a home. We use the orientation variables to test for H2.

Exhibit 10 presents the results for homes that are less than 15 years of age, priced at least $750,000 and located on lots that are at least half an acre. Given the small sample size (241 houses) and the selection criteria, the results must be viewed with some caution. Although San Diego ranks nationally in solar panel installation, the findings do not support the hypothesis of a premium for solar installation (H1.1). One reason could be that although the solar capacity in San Diego is sufficient to power nearly 76,000 homes,[2] with about 1.2 million homes in the county,[3] only about 10% of those homes have solar installations.[4] Another reason could be that, in general, the weather is fair in San Diego, such that many homes lack air conditioning or a heating system. As such, without the cost associated with the central air system, the demand for a more energy-efficient input is low. Additionally, the interaction between solar and the different orientations are statistically insignificant, which fails to support H1.2.

However, the findings suggest that newer custom homes command a premium for those oriented either northeast or southeast at the 5% significance level. Homes facing southeast are priced about 12.8% more compared to directly south-facing homes. While slightly lower, homes oriented in a northeast direction have a 9.6%

Exhibit 9 | San Diego Home

premium over south-facing homes. The preference for an eastward direction, whether southeast or northeast, could be due to the choice of having more indirect sun either in the morning or late afternoon. In particular, there is evidence in support of hypothesis 2 (H2) that builders of custom homes on larger lots have more discretion over orientation and may site accordingly.

Exhibit 10 | 2SGLS Estimation Results: Sample without Repeat Sales (n = 241)

Variables	Coeff.	z-Stat.	Coeff.	z-Stat.
Log of Lot Size	0.090***	4.44	0.090***	4.40
Age	0.058	1.26	0.057	1.18
Age Squared	−0.003	−1.41	−0.003	−1.32
Log of Living Area	0.739***	12.29	0.739***	12.29
Baths	−0.004	−0.27	−0.004	−0.27
Bedrooms	−0.022	−1.26	−0.022	−1.25
Pool	0.164***	7.03	0.163***	6.92
Cul-de-sac	−0.014	−0.68	−0.014	−0.67
Intersection	0.009	0.27	0.010	0.30
Log Dist to Coast	−0.191***	−7.16	−0.191***	−6.54
Log Dist Downtown	−0.126***	−2.93	−0.127***	−2.94
Log Dist Open Space	−0.004	−0.42	−0.004	−0.40
Log Dist Freeway	0.047***	3.10	0.048***	3.03
Log Dist Park	−0.018	−1.19	−0.018	−1.20
Log Dist Elementary	−0.027	−1.35	−0.027	−1.31
Log CAASPP	3.232***	3.57	3.225***	3.34
Days on the Market	0.000	0.86	0.000	0.88
East	0.050	0.96	0.050	0.95
North	−0.025	−0.53	−0.026	−0.56
West	0.068	1.41	0.066	1.35
Northeast	0.096**	2.29	0.094**	2.22
Northwest	0.047	1.12	0.046	1.06
Southeast	0.128***	3.00	0.127***	2.90
Southwest	0.080*	1.85	0.078*	1.75
Solar	−0.028	−0.43	−0.030	−0.45
*Solar*East*	0.031	0.31	0.031	0.31
*Solar*North*	−0.027	−0.28	−0.025	−0.26
*Solar*West*	−0.090	−0.94	−0.090	−0.92
*Solar*Northeast*	−0.088	−1.04	−0.087	−1.02
*Solar*Northwest*	0.005	0.06	0.006	0.08
*Solar*Southeast*	0.030	0.36	0.031	0.37
*Solar*Southwest*	−0.073	−0.87	−0.072	−0.85
Green View	0.135***	3.85	0.262	0.47
Water View	0.222**	2.52	0.222**	2.52
Log Dist Open Space Green View*			−0.002	−0.07
Log Dist Open Park Green View*			−0.013	−0.19
Quarter FE	Yes		Yes	

Exhibit 10 | (continued)
2SGLS Estimation Results: Sample without Repeat Sales (n = 241)

Variables	Coeff.	z-Stat.	Coeff.	z-Stat.
Constant	−23.044***	−3.20	−23.001***	−2.96
rho	0.563***	7.08	0.564***	7.01
Quarter FE	Yes		Yes	
Pseudo R^2	0.935		0.934	

Note:
*$p < 0.1$
**$p < 0.05$
***$p < 0.01$

As for the additional control variables, the number of days a home is on the market is statistically insignificant. While we include the median DOM by ZIP Code instead of the DOM for each home, previous studies note that DOM is often unreliable as agents re-list homes as "new" by taking a listing off and on the market (Miller and Sklarz, 2008, 2012). Moreover, both green and water views are statistically significant in the expected direction. Namely, views of green (parks and open spaces) and water lead to a 13.5% and 22.2% increase in the price of the home, respectively. However, the statistical significance of green view is not robust to the inclusion of the interaction with the distance variables for park and open spaces.

Overall, the results suggest that the orientation of the home is a factor for newer and higher-priced homes built on larger lots. More importantly, estimating a full sample across a wide range of prices may provide misleading results. In particular, for newer and higher-priced homes located on at least half an acre, solar does not add to the price of the home but those facing either southeast or northeast have a premium of about 12.8% and 9.6%, respectively. Additionally, the findings suggest the importance of correcting for the spatial autocorrelation. With the inclusion of the spatial lag, traditional proximity variables, such as distance to downtown and distance to park, become negative as expected. In particular, there is a discount for homes located further from the central business district or parks. Additionally, the premium from being located on an intersection (often also the corner lot) becomes insignificant once the specification includes the spatial analysis.

Conclusion

Builders have taken house orientation into account when siting houses for some time. Whether to capture favorable lighting, minimize exposure to prevailing bad weather, or maximize the potential for solar power generation, orientation factors in as a determinant of housing prices. In this paper, we examine the value of the orientation for single-family homes in San Diego County from 2016 to 2017. The results suggest that there is indeed a premium for houses oriented indirectly along

an east-west axis. Newer and higher-priced houses built on larger lots that face either northeast or southeast are valued higher than south-facing homes. The preference for indirect heat from the sunlight could be due to the lack of air-conditioning in the majority of San Diego homes. Moreover, homes oriented toward the northeast or southwest may benefit from views of the ocean from either the front or back of the property due to the presence of canyons and mesas in San Diego County.

Partially due to a smaller sample of newer homes on larger lots, the results are inclusive regarding a premium for homes with solar panel installation. While the cost of installation has decreased in recent years, only about 10% of homes have solar panel installations in San Diego. The generally fairer San Diego weather could potentially lessen the demand for a more energy-efficient input to lower electrical costs compared to cities requiring air conditioning or a heating system.

In addition to examining the role of the orientation of the house on housing prices, we study the role of location within the block on housing values. Previous studies have generated mixed results regarding the significance of corner locations and cul-de-sacs on housing values. Based on this sample, there is no evidence that location in a cul-de-sac is significant in explaining variation in housing prices. However, San Diego is quite unusual in having such a large percentage of homes (25%) located in cul-de-sacs. It should not be surprising then that location in a cul-de-sac does not command a premium in San Diego County. In an OLS specification, we find some evidence that being at an intersection has a positive and significant impact on housing prices. However, after controlling for spatial autocorrelation, location at an intersection is no longer significant. This result demonstrates the importance of controlling for spatial autocorrelation when performing hedonic price analysis on real estate prices.

Endnotes

[1] https://www.californiasolarstatistics.ca.gov/reports/locale_stats/.

[2] http://cleantechsandiego.org/san-diego-ranks-1-nationally-solar-panel-installations/.

[3] https://factfinder.census.gov/faces/nav/jsf/pages/community_facts.xhtml?src=bkmk.

[4] https://www.californiadgstats.ca.gov/charts/.

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