Real Estate Prices in Los Angeles – A Case Study from Redfin

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Abstract

Real-estate market dynamics in Los Angeles County affect the decision-making framework of all stakeholders involved in the buying or selling process. For first time home buyers and realtors alike looking to expand their market reach, the methodologies presented in this paper add value in this endeavor. Leveraging exploratory data analysis lends itself to comparative metrics between prices and home characteristics not limited to size and year built and expanding into specific characteristics that portray relationships between all variables of interest. To establish and understand these key performance indicators (KPIs) from a selective sample, a reproducible, excel-based model is produced. Limitations are discussed based on the sample size and suggestions are made for further refinement utilizing other sampling methodologies and software packages.

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There are several stakeholders involved in the real-estate decision-making framework. Real-estate corporations and individual decision makers alike are often tasked with resolving where and what to buy as they partake in their search for single family housing properties. However, one must choose an area of focus, especially as a future home buyer. This carefully selected dataset was chosen for a specific geographic region of the Los Angeles County in Southern California. The data is sourced from Redfin as opposed to other real-estate resources due to its ease of public access for MLS (Multiple Listing Service) properties. This dataset is represented by a flat .csv file which has been downloaded at a static moment in time in September 14, 2020; nonetheless, contained herein are all of the relevant parameters in helping to establish trends in the Los Angeles Housing Market. These parameters serve to identify patterns between price, housing type, and location, to name a few variables of interest. Considerations are made for the sample size, as the first 100 listings are examined, thereby extracting an appropriate sample for the ensuing analysis. Establishing pricing patterns by location and disposition of home will be of great benefit to the stakeholders involved.

For example, a realtor might leverage this analysis to target specific zip codes with higher mean home prices. This action could potentially benefit the realtor visa vie an increase in commission from sales. The consumer, on the other hand, may trade neighborhood (zip code) for affordability. One such variable versus another only sheds light on a particular relationship. For this reason, additional variables need to be considered. Furthermore, one may look at the year that a house was built as a strategic advantage or disadvantage. This paper aims to examine these independent (predictor) variables against the dependent variable of price. In so doing, if a strong correlation exists, the model can prove to be beneficial and hold merit.

A similar study has been conducted where “home values vary across neighborhoods. This implies that certain neighborhood characteristics are more desirable than others” (Hipp & Singh, 2014, 254). The goal of the research was to determine if there was a relationship between “New Urbanism—population density, older homes, a lack of concentration of single family units”(Hipp & Singh, 2014, 254). Additionally, the research examined the Playa Vista Community, attributing revitalization to new infrastructure and addition of important technological companies like Youtube, Microsoft, and Fox Sports (Hipp & Singh, 2014, 258). Moreover, this study incorporated a similar dependent variable of home price (Hipp & Singh, 2014, 260).

In a comparable study, analysts sought to determine “how the housing market will function in the post housing market bubble decade. It is a useful time to take another look at how the housing market behaves and what underpins housing prices” (Clark, 2011, 1).

Exploratory Data Analysis

As shown in the accompanying the location and dispersion information confirms that certain disparities exist. The median house price is $739,900, while the average is much higher, $960,246.46. There exists an astounding variance between the minimum and maximum value ($5,519,000.00) and number of days on the market. Since such a large range between data points for days on the market, other variables of interest will be examined further in the paper to establish relationships as they arise.

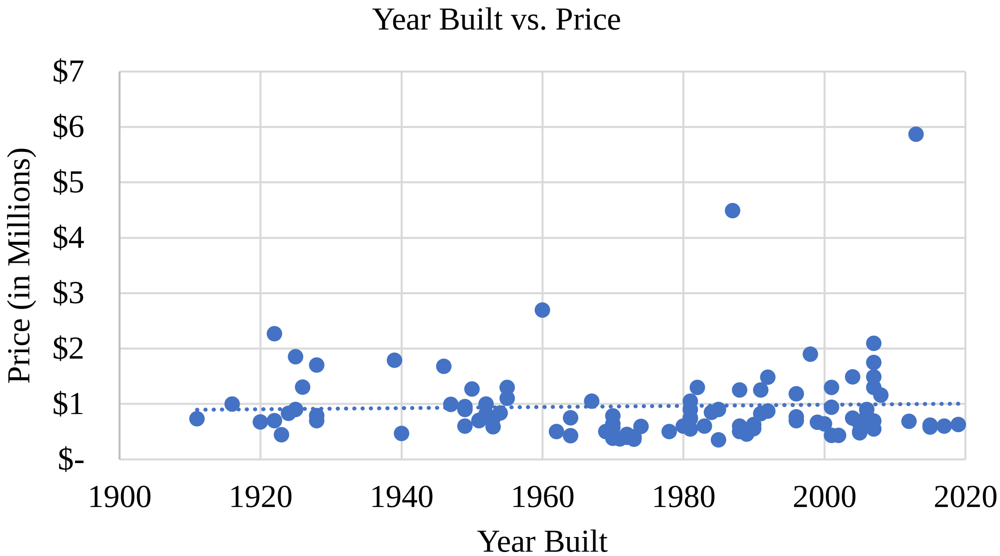
Figure 1.

Location and Dispersion	Price	Days on Market	Year Built
Mean	$ 960,246.46	31	1975
Median	$ 739,900.00	16	1981
Minimum	$ 350,000.00	1	1911
Maximum	$ 5,869,000.00	345	2019
Standard Deviation	$ 761,458.87	50	29

The following figures show varying degrees of correlation in the variables of interest.

Figure 2.

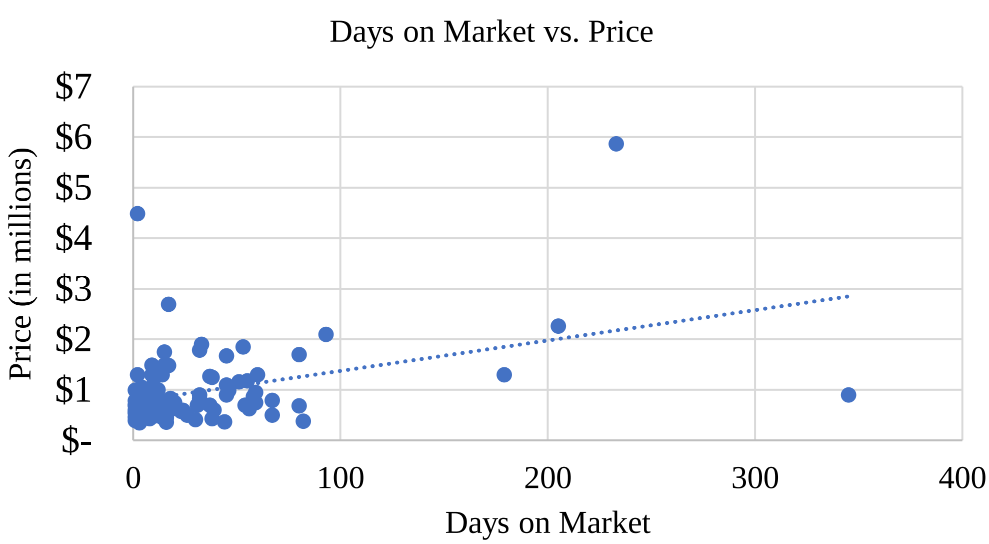
Year Built vs. Price



Note. The year built of the house is loosely correlated with price, offering no significant association or correlation.

Figure 3.

Days on Market vs. Price



Note. Days on market has a greater (more substantial) positive correlation with price.

Generalized Linear Model (GLM)

$Price\ (in\ \$\ USD)$

$$= \beta_0 + \beta_1 Year\_Built \begin{pmatrix} 1 = (1911 - 1932) \\ 2 = (1933 - 1954) \\ 3 = (1955 - 1976) \\ 4 = (1977 - 1998) \\ 5 = (1999 - 2020) \end{pmatrix}$$

$$+ \beta_2 Bedrooms \begin{pmatrix} 1 = (0 - 1)\ Bedrooms) \\ 2 = 2\ bedrooms \\ 3 = 3\ bedrooms \\ 4 = 4\ or\ more\ bedrooms \end{pmatrix} + \beta_3 HOA(Y|N)$$

$$+ \beta_4 Region\_in\_LA\_County \begin{pmatrix} 1 = Antelope\ Valley \\ 2 = Los\ Angeles\ (city\ of) \\ 3 = San\ Fernando\ Valley \\ . \\ . \\ . \\ 10 = West\ Los\ Angeles \end{pmatrix}$$

$$+ \beta_5 Housing\_Type \begin{pmatrix} 1 = Single\ Family \\ 2 = Townhouse \\ 3 = Condo/Co - op \\ 4 = Multi - Family \end{pmatrix} + \varepsilon$$

where $Price$ is the variable of interest (the dependent variable);

Independent variables: *Year_Built, Bedrooms, Region_in_LA_County, Housing_Type*

β_0 is the intercept, or constant offset term;

$\beta_{(1\ to\ i)}$ is the regression coefficient; and

ε is the error factor associated with each regression coefficient.

In this generalized linear model (GLM), the variable of interest is Price (in $USD). It is the variable (*y*) that is dependent on the following independent variables (*x*) ranked in descending order of impact. Year_Built has a higher positive correlation on selling price as newer homes are “selling at higher prices than those that were built in the past” (Manausa, 2012). Lastly, the Region_in _LA_County is of a more categorical nature; thus, while this does illustrate price dynamics by market location, examining this data last fits the model more appropriately.

Table 1
Characteristics of 100 Housing Units in Los Angeles County

Variable	Population *N(%)* (N=100)	Type: Single Family *n(%)* (n=48)	Type: Townhouse *n(%)* (n=10)	Type: Condo/Co-op *n(%)* (n=38)	Type: Multi-Family *n(%)* (n=4)	*P-Value**
Year Built						<.0001
1911-1932 (1)	13 (13%)	8 (17%)	0 (0%)	1 (3%)	4 (100%)	
1933-1954 (2)	15 (15%)	15 (31%)	0 (0%)	0 (0%)	0 (0%)	
1955-1976 (3)	19 (19%)	6 (13%)	0 (0%)	13 (34%)	0 (0%)	
1977-1998 (4)	27 (27%)	10 (21%)	5 (50%)	12 (32%)	0 (0%)	
1999-2020 (5)	26 (26%)	9 (19%)	5 (50%)	12 (32%)	0 (0%)	
Bedrooms						<.0001
0-1 bedrooms (1)	12 (12%)	0 (0%)	0 (0%)	12 (32%)	0 (0%)	
2 bedrooms (2)	32 (32%)	8 (17%)	5 (50%)	18 (47%)	1 (25%)	
3 bedrooms (3)	31 (31%)	22 (46%)	3 (30%)	6 (16%)	0 (0%)	
4 or more bedrooms (4)	25 (25%)	18 (38%)	2 (20%)	2 (5%)	3 (75%)	
HOA						<.0001
Yes (1)	56 (56%)	9 (19%)	9 (90%)	38 (100%)	0 (0%)	
No (0)	44 (44%)	39 (81%)	1 (10%)	0 (0%)	4 (100%)	
Region in Los Angeles County						<.0001
Antelope Valley (1)	1 (1%)	1 (2%)	0 (0%)	0 (0%)	0 (0%)	
Los Angeles (city of) (2)	22 (22%)	9 (19%)	0 (0%)	10 (26%)	3 (75%)	
San Fernando Valley (3)	18 (18%)	7 (15%)	3 (30%)	8 (21%)	0 (0%)	
San Gabriel Valley (4)	13 (13%)	9 (19%)	1 (10%)	3 (8%)	0 (0%)	
Santa Clarita (5)	10 (10%)	8 (17%)	1 (10%)	1 (3%)	0 (0%)	
South Bay (6)	12 (12%)	6 (13%)	2 (20%)	4 (11%)	0 (0%)	
South Los Angeles (7)	1 (1%)	1 (2%)	0 (0%)	0 (0%)	0 (0%)	
Southeast Los Angeles (8)	4 (4%)	3 (6%)	1 (10%)	0 (0%)	0 (0%)	
West Hollywood (9)	4 (4%)	0 (0%)	0 (0%)	4 (11%)	0 (0%)	
West Los Angeles (10)	15 (15%)	4 (8%)	2 (20%)	8 (21%)	1 (25%)	

** P-values based on Pearson chi-square test of association.*

Table 1 represents the characteristics by housing type (Single Family, Townhouse, Condo/Co-op, and Multi-Family) for the sample population (*n* = 100). 48 of these 100 homes sampled from the redfin dataset are single family. 10 of them are town homes. 38 are condo/co-ops, and 4 are multi-family housing units. Of the 100 sampled herein, 13% of these homes were built between the years of 1911-1932. 15% were built between 1933-1954. 19% were built between 1955-1976. However, more than half of these homes (53%) were built between 1977-2020. Notwithstanding, an interesting characteristic to note is that of single-family homes, where most of these properties (31%) were constructed between 1933-1954. The original dataset contains the specific year as it pertains to each row; however, these years were bucketed for the sake of a more standardized model.

The most common number of bedrooms are 2 (31% of the dataset). 46% of single-family homes are known to have 3 bedrooms. 50% of the 10 town homes in this sample have 2 bedrooms. What stands out the most in the “Bedrooms” variable is that 75% of the multi-family homes sampled have 4 or more bedrooms. This is proportional to the scale (size) of the housing unit.

The data also examines whether each housing type has an HOA or not. 56% of the properties sampled do have an HOA, whereas 44% do not. This would suggest, at least on a high level, that most of the properties are condominiums and/or town-homes. However, upon closer examination, this is not the case. The dataset presents an equal number of condominiums and town-homes (n = 48) as single-family homes. The 19% visibility of homeowner’s associations in single family homes contributes to the spike of HOA prevalence across this sample.

Furthermore, Los Angeles County presents a wide range of observable data, with 50 cities (accounting for half of the observable records) in this dataset. Shifting the focus from city to region produced ten meaningful areas of focus. Whereas Antelope Valley and South Los Angeles showed no material (not statistical) significance, that 10% of all town homes in this sample are sold there. 30% of this type of home exists in this sample for the San Fernando Valley (the region selling that sells the highest percent of this type of home in the sample). Moreover,50% of the data exists in the city of Los Angeles, San Fernando Valley, and Santa Clarita, which account for 30% of all regions represented here. Los Angeles (city of) accounts for 22%, San Fernando Valley - 18%, and Santa Clarita - 10%, respectively. South/ Southeast Los Angeles, West Los Angeles (and West Hollywood), as well as the Antelope Valley comprise the remaining 50% of all housing units represented in this sample. 75% of all multi-family housing units exist in the city of Los Angeles proper. This table shows statistical significance between the variables of interest and housing type at an α level of .05 (P <.0001).

Limitations

In order to yield a net benefit visa vie reproducibility in subsequent iterations of the methodologies described herein, the limitations pertaining to this dataset warrant further examination to mitigate against pitfalls in further repeat studies of a similar magnitude. To accomplish this task, we must first discuss these limitations in terms of accuracy versus precision. The data was sourced as a static .csv file on the fourteenth of September 2020, assuring precision through this date only. Its accuracy cannot be fully guaranteed for the following reasons. Real estate data changes in real time, as houses are bought and sold. Thus, a more refined model should take the same data into account, but not through a static .csv file. For example, statistical packages and libraries in R Studio (i.e., read .csv, readr, etc.) are capable of loading this data repeatedly over the course of a few weeks while establishing summary statistics, but with the added bonus of tracking variances in results as the housing market changes.

Furthermore, redfin.com, while rich in location-based housing information nationwide, does not lend itself to the best exporting capabilities to meet the needs of full size and scope for any given market. Consequently, there exists “a 350 home cap on data downloading” (Murphy, n.d.). Thus, restricting the dataset to a sample size of the first $n = 100$ rows of data without a proper randomization technique, creates yet another challenge in data integrity. To obtain a sample that is more representative of the population as a whole, a simple random sample would suffice. Here, the researcher could open the .csv file, save it as an .xslx file to keep the formulas, and create a new column (A) and fill the cells down in ascending order (0,1,2,3…350). The adjacent column (B) could contain a formula =RANDBETWEEN(A2,A352) where each cell contains a value between the top and bottom cell in the dataset. Filtering the new column down to values zero to one hundred will yield the desired results.

Lastly, creating a significant model for home prices in Los Angeles County based on limited information at only one moment in time presents the bottleneck of bucketing or classifying the many cities within Los Angeles County. Out of these 100 observations, the report yielded 50 unique cities, which would be unsustainable for a linear regression model. Initially, ten cities with the highest average home price were chosen with the intent of illuminating insights on the composition of home prices across the county of Los Angeles. However, to mitigate against any potential bias resulting from this sample, a better methodology was produced, where the cities were bucketed into twelve geographic regions. This was further refined and the geographic regions were narrowed down to ten categories for a concise, yet, more robust and accurate model.

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