Effects of Structural Characteristics on House Prices

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1 Executive Summary

This report aims to investigate the variables that influence house prices. The variables available for analysis include, house size, number of bedrooms, number of bathrooms, land size, age and presence of a fireplace. It was concluded that the main variables that influence house prices were, house size and its number of bathrooms; the age and presence of a fireplace were also used in obtaining an accurate prediction of house prices. This is modelled through the equation:

$$\ln Price = \beta_0 + \beta_1 Size + \beta_2 Baths + \beta_3 Fireplace + \beta_4 \log_{10} Age + \varepsilon$$

2 Introduction

Owning a house is one of the biggest investments a person can make. As such, it is of great interest to prospective buyers, sellers and lenders to accurately predict the price of a home. There are a range of models and techniques that attempt to predict the price of a home, from observational appraisals all the way to machine learning models[2]. One method widely studied is that of hedonic pricing. A Hedonic Pricing Model (henceforth, HPM) is a model that attempts to estimate the price of a good by taking its observable characteristics and then weighting them according to their relative impact on the price. Models utilise a range of measures that can be categorised into several groups, namely structural, neighbourhood, and environmental.[3] Hearth and Maier, in a literature review of HPMs for real estate, had identified that the neighbourhood and environmental factors were generally over-researched. While social factors and the "implicit value of structural characteristics" was under-researched.[1]

2.1 Related Work

There appears to be a consensus that creating a HPM, particularly focussing on structural characteristics, has problems with heteroskedasticity. This means that linear models may not be entirely appropriate to estimate the response. This was sought to be relieved by Selim, Limsombunchai and Malpezzi by using a semi-logarithmic form wherein the response variable is transformed by the natural log.[2, 3, 4] Additionally, Malpezzi explains that this effectively allows value added to the house to be proportional to other variables in the model and for an easier interpretation of coefficients such that the coefficient of a measure is the percentage change for 1 unit difference in the measure.[3] In the end Selim concluded that water system, presence of a pool, the type of house, number of rooms, house size, locational characteristics and building type were the most significant variables to affect house prices in the country of Turkey.[4]

2.2 Data Set

The data set contains data on houses in Saratoga County, New York; collected by Candice Corvetti in 2006. It contains 1063 randomly selected observations collecting data on house price, size in square feet, number of bathrooms, number of bedrooms, the presence of a fireplace, land size in acres and the age of the house in years.

2.3 Aim

The aim of this report is to fit a model that will attempt to determine how the price of a house depends its structural characteristics. Significant variables that appear in the Turkish model will be explored in the Saratoga data set to see if they also play a significant role in predicting house price.

3 Methodology

The methodology to be used in this report will be split into two parts. Data exploration and model fitting.

3.1 Data Exploration

Firstly, the scatter plots between independent and dependent variables will be visually analysed to identify relationships and distribution of data. Strangely distributed data will attemp to be transformed to find a linear relationship to the price. After, scatter plots between independent variables will be visually analysed to quickly identify multicollinear variables. Additionally, correlation analysis will be used to supplement the visual analyses. This process will aim to identify redundant and non-contributing variables that we may expect will be excluded from the final model. Variables that are suspected to have interaction are investigated by running linear regressions with only those interaction terms and analysing the interaction plots. If an interaction effect is apparent then that interaction term will be considered in model fitting.

3.2 Model fitting

Model fitting will be done with backwards elimination, including found interaction variables. Then, the collinear and redundant variables will be removed from the model and tested using the F-test to check for a better fit. Then normal backwards elimination, in which where variables eliminated from the model if they have a low significance to the model, is applied.

4 Results

4.1 Data Exploration

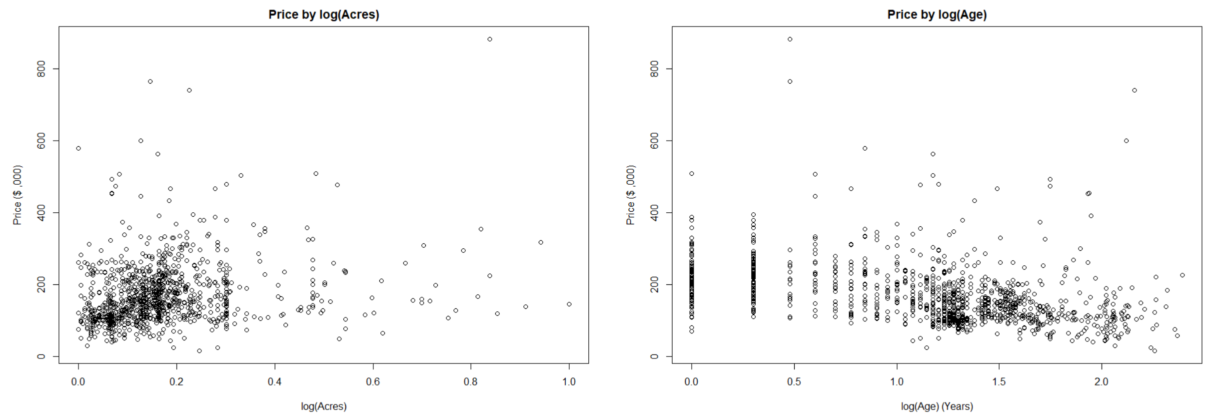
Below are the relationships between the Price and independent variables.
Correlation data in appendix figure 1 and 2.

- Size - exhibits a strong, positive linear relationship. (correlation: 0.77)
- Baths - exhibits a moderate, positive linear relationship. (correlation: 0.67)
- Bedrooms - exhibits a moderate linear relationship (correlation: 0.47)
- Fireplace - exhibits a weak, positive linear relationship - houses with a fireplace have a higher range of price, as well as a higher mean (correlation: 0.41) (*Correlation data in appendix figure 3.*)
- Acres - little to no linear relationship - data is heavily right skewed
  - acres are all clustered closer to 0 (correlation: 0.18)
- Age - little to no linear relationship - heavily right skewed
  - majority of properties are grouped towards 0 age (correlation: -0.26)

Acres and age appeared to show a right skewed nature, therefore a logarithmic transformation was applied in order to achieve a more normal distribution.*Figure 4 - Correlation coefficients for log transformed data*

Price by Acres and Price by Age

Price by log10(Acres) and Price by log10(Age)

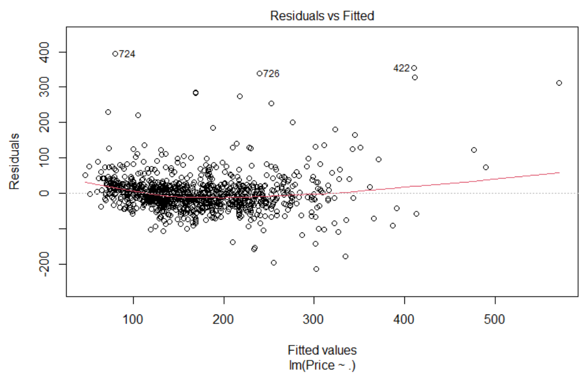


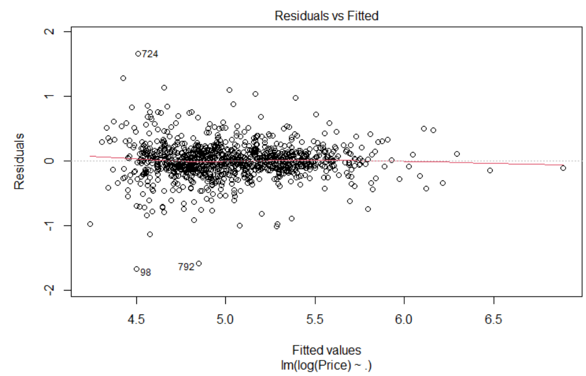
Now we will find collinear variables, firstly by visually inspecting the plot of all variables (*see appendix fig. 2*). From this we can observe that the following have correlations of:

- Size and Baths (correlation: 0.77)
- Size and Bedrooms (correlation: 0.67)
- Baths and Bedrooms (correlation: 0.51)

Interaction terms involving the fireplace metric were investigated as it was the only categorical variable available to us. Only the size variable appeared to have somewhat of an interaction as shown below. Black dots showing no fireplace, and red dots showing the presence of a fireplace. Fireplaces seem to appear in houses of all sizes but as houses become larger, the more prevalent a fireplace becomes An analysis of variance on this interaction returns a p-value of p=3.19e-10.

4.2 Model fitting





First, the full model (without interactions) was fitted, without the interaction. And the residuals were plotted. The errors to the fitted line were not constant and this was reflected in the high Residual Standard Error (52.15), thus confirming the presence of heteroskedasticity described in the literature. As suggested by previous studies, I applied a natural log function to the response variable. This model returned a much lower RSE of 0.279, thus indicating the response variable much closely follows a log relationship to the independent variables in the model. Next, the starting model(with interactions) for is given by the formula:

$$\ln Price = \beta_0 + \beta_1 Size + \beta_2 Baths + \beta_3 Bedrooms + \beta_4 Fireplace + \beta_5 \log_{10} Acres + \beta_6 \log_{10} Age + \beta_7 Fireplace * Size + \varepsilon$$

Through backwards elimination, the variables of bedrooms, fireplace, acres and fireplace & size interaction are eliminated. thus the final model is:

$$\ln Price = \beta_0 + \beta_1 Size + \beta_2 Baths + \beta_3 Fireplace + \beta_4 \log_{10} Age + \varepsilon$$

The final model has an RSE of 0.2819, and adjusted R-squared of 0.6087.

5 Discussion

Due to the low correlations of fireplace we can assume that it is likely to be a non-contributing variable and unlikely to come up in the final model

age and acres might have been able to be transformed in order to find a relationship - not really

Due to the multicollinearity shown by size, baths and bedrooms variables, we will likely exclude one or two of these variables from the final model. The variable with the highest correlation to the price is Size. Therefore Baths and Bedrooms may end up exluded in the final model.

At this point, the data would have pointed to removing all but the size variable from the model.

perhaps a more thorough data exploration with more interaction terms + interaction terms with continuous vars in bins + interaction chosen may not have been overly relevant? and more in depth visualisations would aide in the creation of the final model.

Final Model -

References

[1] Herath, S. K. Maier, G. (2010). The hedonic price method in real estate and housing market research. A review of the literature.. Institute for Regional Development and Environment (pp. 1-21). Vienna, Austria: University of Economics and Business.

[2] Limsombunchai, V. (2004). House price prediction: Hedonic price model vs. artificial neural network. New Zealand Agricultural and Resource Economics Society Conference, 25-26 June 2004. Blenheim, New Zealand: New Zealand Agricultural and Resource Economics Society.

[3] Malpezzi, S. (2003). Hedonic pricing models: a selective and applied review. Housing economics and public policy, 1, 67-89.

[4] Selim, S. (2008). DETERMINANTS OF HOUSE PRICES IN TURKEY: A HEDONIC REGRESSION MODEL . Dogus Universitesi Dergisi , 9 (1) , 65-76 . Retrieved from

Appendix.

Figure 1 - Correlation coefficients for untransformed data

	Price	Size	Baths	Bedrooms	Fireplace	Acres	Age
Price	1.00	0.77	0.67	0.47	0.41	0.18	-0.26
Size	0.77	1.00	0.74	0.67	0.47	0.22	-0.23
Baths	0.67	0.74	1.00	0.51	0.45	0.13	-0.40
Bedrooms	0.47	0.67	0.51	1.00	0.30	0.15	-0.04
Fireplace	0.41	0.47	0.45	0.30	1.00	0.06	-0.24
Acres	0.18	0.22	0.13	0.15	0.06	1.00	0.01
Age	-0.26	-0.23	-0.40	-0.04	-0.24	0.01	1.00

Figure 2 - All plots

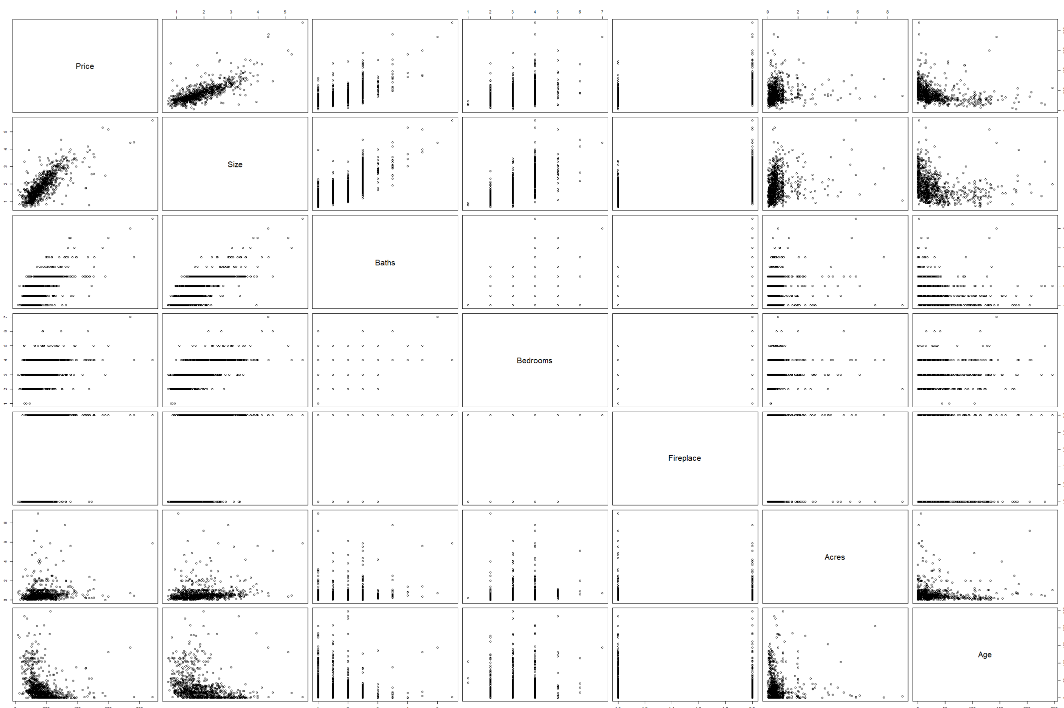


Figure 3 - Price by Fireplace boxplot

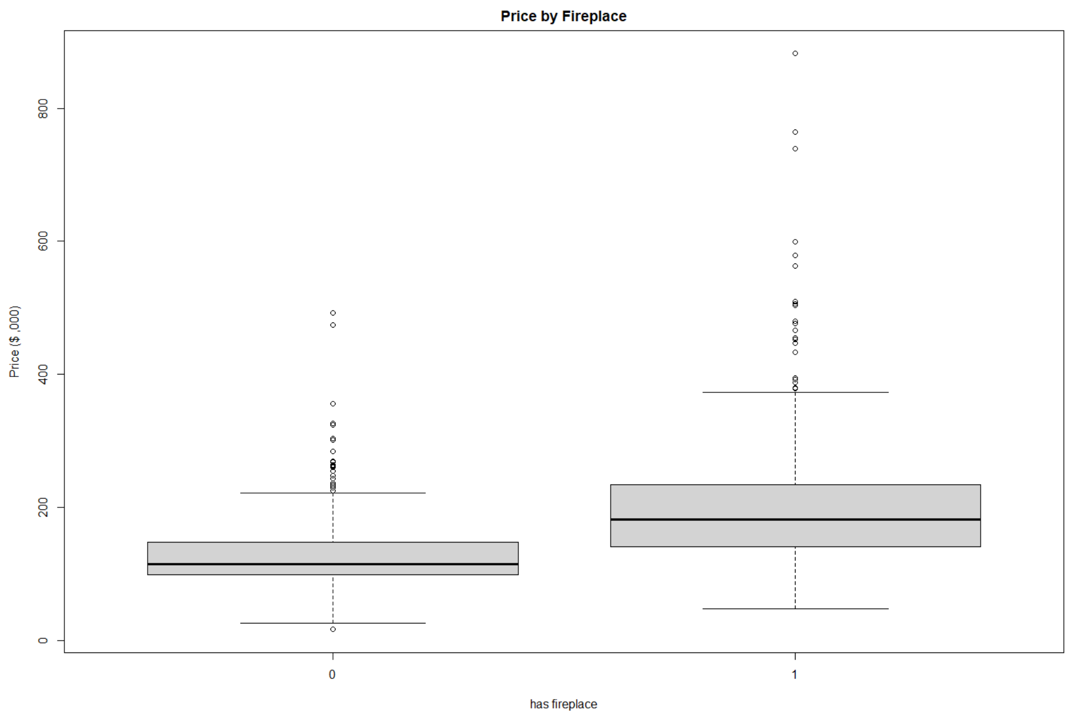


Figure 4 - Correlation coefficients for log transformed data

	Price	Size	Baths	Bedrooms	Fireplace	Acres	Age
Price	1.00	0.77	0.67	0.47	0.41	0.22	-0.39
Size	0.77	1.00	0.74	0.67	0.47	0.28	-0.42
Baths	0.67	0.74	1.00	0.51	0.45	0.17	-0.53
Bedrooms	0.47	0.67	0.51	1.00	0.30	0.22	-0.18
Fireplace	0.41	0.47	0.45	0.30	1.00	0.12	-0.29
Acres	0.22	0.28	0.17	0.22	0.12	1.00	-0.08
Age	-0.39	-0.42	-0.53	-0.18	-0.29	-0.08	1.00

Figure 5 - Full model + Fireplace:Size Statistics

$$\ln Price = \beta_0 + \beta_1 Size + \beta_2 Baths + \beta_3 Bedrooms + \beta_4 Fireplace + \beta_5 \log_{10} Acres + \beta_6 \log_{10} Age + \beta_7 Fireplace * Size + \varepsilon$$

```
Residual standard error: 0.282 on 1055 degrees of freedom
Multiple R-squared:  0.611,	Adjusted R-squared:  0.6084
F-statistic: 236.7 on 7 and 1055 DF,  p-value: < 2.2e-16
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Figure 6 - Final model Statistics

$$\ln Price = \beta_0 + \beta_1 Size + \beta_2 Baths + \beta_3 Fireplace + \beta_4 \log_{10} Age + \varepsilon$$

```
Residual standard error: 0.2819 on 1058 degrees of freedom
Multiple R-squared:  0.6101,	Adjusted R-squared:  0.6087
F-statistic:   414 on 4 and 1058 DF,  p-value: < 2.2e-16
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Figure 6 - Final model Statistics

$$\ln Price = \beta_0 + \beta_1 Size + \beta_3 Baths + \beta_5 Fireplace + \beta_7 \log_{10} Age + \varepsilon$$

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Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)   4.23022    0.04591  92.134  < 2e-16 ***
Size          0.31402    0.01933  16.247  < 2e-16 ***
Baths         0.13768    0.02097   6.564 8.19e-11 ***
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FireplaceYes  0.11638    0.02031   5.729 1.32e-08 ***
Age          -0.09263    0.01791  -5.172 2.77e-07 ***
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