# Analyzing the Factors that Determine Housing Prices in Beijing and Predicting Trends in the 21st Century: The Building Structures and The Number of Living Rooms as Prime Drivers of Price Surges*

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This report uses Kaggle's beta API, and collects the Housing price of Beijing from 2011 to 2017, fetching from Lianjia company. Taking the average price by square as the main observation object, and analyzing the potential factors affecting Beijing's housing prices based on geographical coordinates, building type, number of kitchens, and other characteristics. The study found that building structures and the number of living rooms have the most significant impact on surging house prices. These results may have significance in the trend prediction of Beijing housing prices and provide a reference for personal home purchase decisions and economic management.

## Table of contents



*Code and data are available at: https://github.com/zxc0707/Beijing-housing-price

# Introduction

Beijing, located in northern China and the capital, has a rich cultural heritage and humanistic resources from a historical perspective. In the past 20 years, citizens' demand for housing has been stimulated by the growing population and economic development, with the specific growth rate soaring at an average annual rate of 43%. (Y. Li, Xiang, and Xiong 2020) Beijing is the representative city of China's real estate transaction volume. The phenomenon of housing price bubbles has been proven to occur frequently in Beijing by empirical analysis (Chen 2012). The specific manifestation is that the prices of land and houses are extremely high, which is inconsistent with their use value. Unfortunately, residents do not receive housing benefits that keep pace with the policies, which induces the impact of housing affordability on the social and economic sustainability of cities. (Wang, Hoon, and Lim 2012) Moreover, the increase in housing prices brought about by urban reform comes at the expense of the mental health of urban residents. Some groups of people will have negative psychological effects on housing pressure. For example, men are more likely to suffer from psychological distress than women and even induce depression. (Lai and Lee 2006) A large number of studies on promoting the surge in housing prices show that various factors affect housing transaction prices in Beijing. From an economic perspective, land transaction prices and taxes have a decisive impact on housing transaction prices. (He et al. 2010) In addition, the influence of environmental factors is reflected in the location of housing in the city center, nearby transportation convenience, and distance from hospitals, which are all positively related to housing prices (S. Li, Chen, and Zhao 2019). Analyzing housing prices in Beijing through the study of multiple factors

for forecasting trends is of great assistance and importance to potential home buyers in their economic management and purchasing decisions.

This report aims to analyze the degree of housing price differences caused by various housing characteristics from the perspective of hedonic determinants, then use the results to predict the direction of Beijing housing prices in the 21st century based on the late 20th century as the dividing line. Hedonic determinants in this case refer to differences in housing prices due to differences in housing space, materials, and other factors that bring residents experience. (Duan et al. 2021) Here, I hope to find some characteristics that have a clear decisive effect on housing prices and use modeling and sketching to show the order of dominance between 7 properties that affect the price. This perspective of horizontally discussing many potential factors separately according to the particular time points of the 20th century to the 21st century has not been discussed deeply in prior papers and may be of interest to economists, policymakers, and home appraisers. (Starr 2012)

Using Kaggle's beta API, information related to Beijing housing prices was collected and assembled into a huge data set for analysis. This housing information from 2011 to 2017 was collected and displayed on Lianjia.com, which is a gap in this database because 6 years of data are scarce for studying housing issues. Basic information about each housing such as geographical location, number of bathrooms, etc. are recorded by relevant staff of Lianjia Company using tables. The final dataset used was the result of cleaning and creating new variables based on the existing observations and was analyzed according to my main research purpose.

In the Data section, the data set collected from Kaggle's beta API will be introduced and explain how to clean, place, and create new variables to achieve appropriate analysis. In this section, I will discuss the datasets, variables, and methods used to process the raw data. Next, for the Model part, I will compare the impact of different housing factors on prices under distance distribution. I will discuss the model and its impact on the interpretation of the aims. Some image sketching is shown to provide necessary explanations and evidence for predicting Beijing housing prices by taking the century junction as a time node in the Result part. Finally, the findings of a number of living rooms and the building structures that are seen as dominant in the surge in housing prices in Beijing will be discussed with implications and shortcomings of this report in the Discussion section.

# Data

## Dataset

In order to accomplish the goals set in this report, the data package used was downloaded from a post titled "Housing price in Beijing" on Kaggle, an open database platform. Kaggle is an online community platform for data management and statistics enthusiasts, which categorizes and stores large amounts of data sets and information. Also, it allows users to upload portfolios

to the online platform and access them through the website's beta API. The original data collected in this article contains 318851 house information and 26 variables, which involve house numbers and various attributes such as house size, construction time, total price, etc.

Regarding the cleaning of the original data set, I first extracted 14 variables that have potential contributions to this report from the 26 variables in the original data set. Besides, some invalid data in the original data set such as missing data and "NaN" are cleared since missing values and these meaningless characters will affect the analysis work. Next, I set the year 2000 as the center point of time and organized the data. I first set the overall research time range from 1980 to 2020 and set each 10 years as a group, such as 1980-1990, 1990-2000, etc. Randomly select 125 observations from each of these 4 groups to form a total of 500 data. In addition, I also removed 5 rows of data that have an impact on the model establishment from the overall 500 observations based on diagnosing influential cases indicated by the influence plot. Detailed explanations can be found in the Appendix.

There are many similar data sets used to analyze housing prices in the open platform Kaggle, two of which are similar to the data sets selected for this report. The two data sets titled "Boston Housing" and "New York City Airbnb Market" also have a large collection of variables that can be used to infer underlying factors in housing prices. However, Beijing's housing prices are more representative than those in American cities since the year-to-year span is large. This advantage is more conducive to me inferring trends when comparing house prices horizontally.

## Variables and Features

Table 1: Data Features

| Feature | Description |
|---|---|
| id | The id of transaction |
| Lng | The longitude in coordinates |
| Lat | The latitude in coordinates |
| totalPrice | The total price (unit is ten thousands RMB) |
| price | The average price by square(unit is RMB) |
| square | The square of house(unit is square meter) |
| livingRoom | The number of living room |
| drawingRoom | The number of drawing room |
| kitchen | The number of kitchen |
| bathroom | The number of bathroom |
| buildingType | 4 types of building (1/2/3/4) |
| buildingStructure | 6 types of materials (1/2/3/4/5/6) |
| constructionTime | The time of construction |
| elevator | whether there is an elevator (1/2) |

Table 2: Details of Several Data Features

| Feature | Details |
|---|---|
| buildingType | tower(1), bungalow(2), combination of plate and tower(3), plate(4) |
| buildingStructure | unknown(1), mixed(2), brick and wood(3), brick and concrete(4), steel(5), steel-concrete composite(6) |
| elevator | no elevator(0), has elevator(1) |

The original data set had a total of 26 variables, which I reduced to 14 variables that are relevant and manageable to the aims of this report. The specific name and description of each variable can be found in Table 1. Among these 14 variables, 3 variables represent different meanings according to different numbers of entries in the data set, namely "buildingType", "buildingStructure" and "elevator". The specific explanation can be separately found in Table 2.

Table 3: Details of New Variables

| Variable | Description |
|---|---|
| dif_lng | Straight-line distance from the center of Beijing in Longitude |
| dif_lat | Straight-line distance from the center of Beijing in Latitude |
| dif_cor | Straight-line distance from the center of Beijing |

In this research report, I try to use the geographical coordinates given in the data set to determine whether Beijing housing prices are related to the distance from the center of Beijing. The specific method is to take the architectural coordinates of downtown Beijing, which is (39.901996392, 116.38833178)(latitude.to n.d.)as the center of the circle. Then create variables "dif_lng" and "dif_lat" by subtracting the center coordinates from the latitude and longitude coordinates given in the data set and taking the absolute values respectively. Then, according to the Pythagorean theorem(Maor 2019), the square root of "dif_lng" and "dif_lat" of each observation is calculated to obtain the straight-line distance between each house and the center of Beijing. Descriptions of the 3 created variables can be found in Table 3

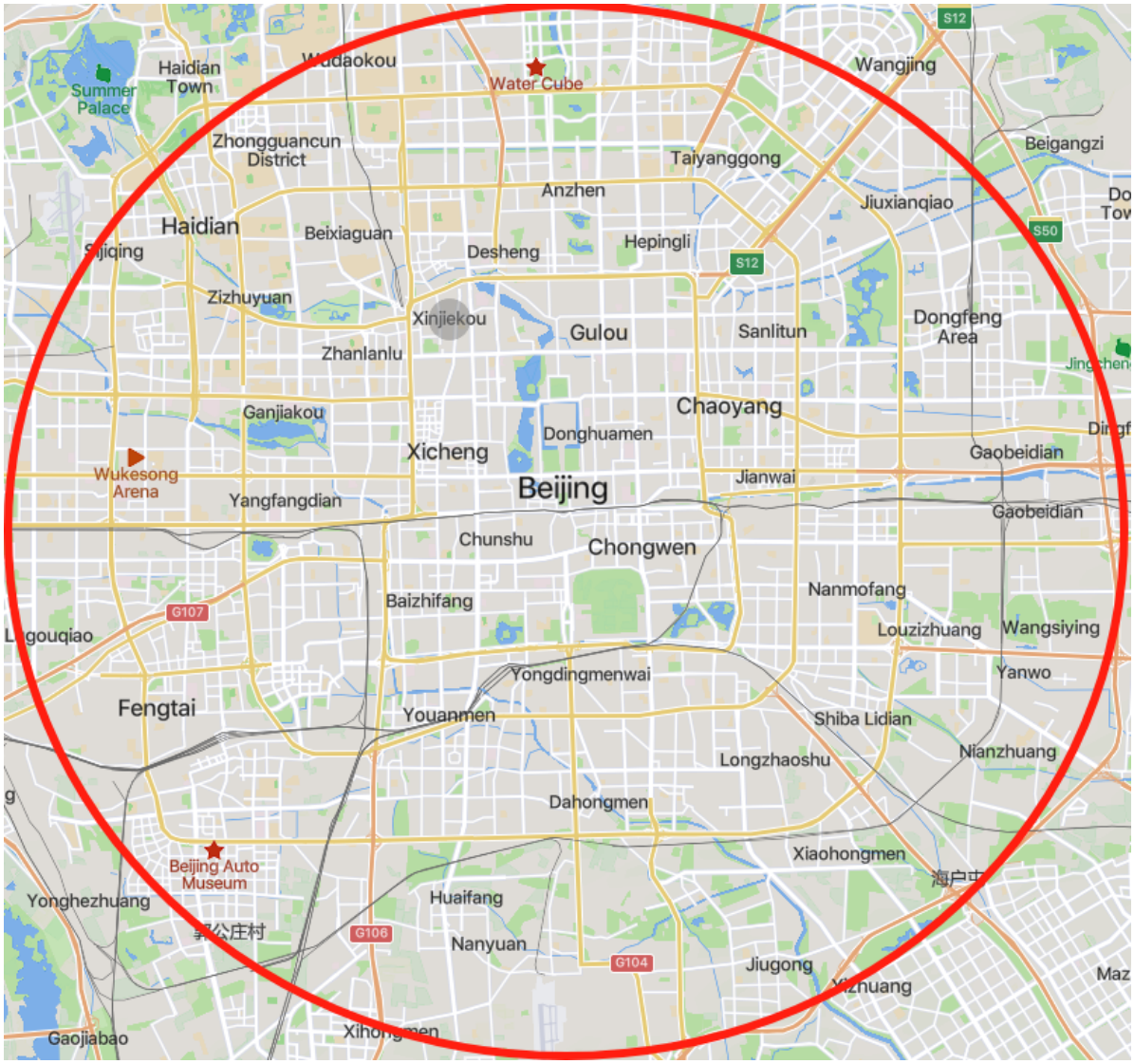



Figure 1: A circle with the center of Beijing as the center

The relationship between variables in the data set is mainly reflected in two aspects. First, there is a positive correlation between the number of various rooms and the price per square, which means that the more the number of living rooms, drawing rooms, kitchens, and bathrooms, the more expensive the price will be. Second, building materials and building types led by the times are related to prices per square. This shows that there is a big difference between the combination of plate and tower, which is also made of brick and wood, before 2000 and after 2000. These two dependencies will be explained in detail in the Result section.

All data manipulated and presented in this report were sourced from the datasets (Ruiqurm

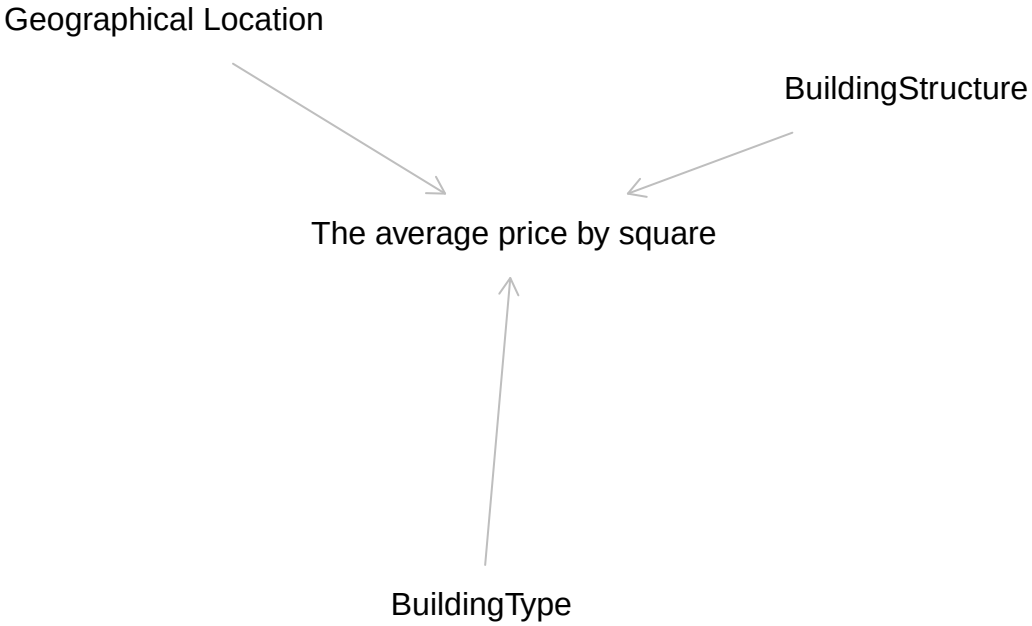
2024) in Kaggle open website. The data processing, and analyzing for this report is using R (R Core Team 2024a) along with other support packages tidyverse(Wickham et al. 2019), psych(William Revelle 2024), lubridate(Grolemund and Wickham 2011), knitr(Xie 2023), ds4psy(Neth 2023), scales(Wickham, Pedersen, and Seidel 2023), ggplot2(Wickham 2016), car(Fox and Weisberg 2019), stats(R Core Team 2024b), readr(Wickham, Hester, and Bryan 2024), dplyr(Wickham et al. 2023), dagitty(Textor et al. 2016).

### Missing Data

The data collected and used in this article have certain limitations, which will have varying degrees of impact on the conclusions I draw based on the analysis. Since Lianjia's collection time for this data set is limited to the six years from 2011 to 2017, more data before 2010 and after 2017 cannot be obtained and added to the analysis. This limitation also illustrates the impossibility of historical analysis relative to the macro scale. Next, the original data set was missing some variables that might have yielded more significant results. This includes but is not limited to, the direction in which the apartment faces as it relates to sunlight, as well as transaction attributes that are highly relevant to policy impacts. In addition, the irrelevances of many entries in the original data will be small and lead to inaccurate model building. Specifically, part of the data in the variables "constructionTime" and "buildingType" is marked as meaningless characters such as "NaN" due to missing data. In addition, there is also a lot of data outside the normal range for the variables "price" and "totalPrice". When this data is removed, statistical models and plots will be affected.

## Model

For this report, I tried to use a linear regression model in order to confirm that the location of the house, building Type, and building Structure have a linear relationship with the average price by the square of the room. This is because linear regression models provide coefficients that represent the relationship between independent and dependent variables. These coefficients are interpretable and suitable for building models on a single variable while fixing multiple variables.(Weisberg 2005) The directed acyclic graph is constructed to visualize what I want to discuss and Model variables. This helps to clearly show the relationship between these variables.




$$Y_1 = \beta_0 + \beta_1 X + \epsilon \tag{1}$$

In my first linear regression model, I study the relationship between Beijing housing prices (Price) and the distance to the center of Beijing (dif_cor) as a single variable. $Y_1$ represents the average price by square in different geographical locations. The unit is expressed in latitude and longitude coordinates, which means that 0.1 is equal to 11km (Tembhekar and Sakhare, n.d.). $\beta_0$ represents intercept, which is the average price by square when the distance between the house and the center of Beijing is 0. $\beta_1$ represents the coefficient for the variable dif _cor. $X$ represents the value of the independent variable "dif_cor" which is equal to each observation of the straight-line distance from the center of Beijing. $\epsilon$ represents the error term. The whole linear equation can be found in Equation 1

$$Y2 = \beta_0 + \beta_1 X + \beta_2 L + \beta_3 D + \epsilon \tag{2}$$

$$Y3 = \beta_0' + \beta_1' X + \beta_2' L + \beta_3' D + \epsilon' \tag{3}$$

$$Y4 = \beta_0'' + \beta_1'' X + \beta_2'' L + \beta_3'' D + \epsilon'' \tag{4}$$

The second model is a Multiple linear regression. This model studies the relationship between different Beijing housing prices (Price) and the two variables of Beijing center distance (dif_cor) and building type (buildingType). In this model, I also added the number of Living

rooms (livingRoom) and Drawing rooms (drawingRoom) as fixed variables. $Y_2$,$Y_3$,$Y_4$ respectively represent the tower, the combination of plate and tower, and the average price by the square of the plate. The units are expressed in latitude and longitude coordinates. $\beta_0$, $\beta_0'$, $\beta_0''$are the intercept coefficients for each building type, that is, when the distance between the house and the center of Beijing is 0, the average price by the square of the three different building types.$\beta_1$, $\beta_1'$, $\beta_1''$are the coefficients for the 'dif_cor' variable for each building type. $\beta_2$, $\beta_2'$, $\beta_2''$are the coefficients for the "livingRoom' variable for each building type. $\beta_3$, $\beta_3'$, $\beta_3''$ are the coefficients for the 'drawing room' variable for each building type. X represents the value of the independent variable"dif_cor" which is Equal to the straight-line distance between each observation and the center of Beijing. L means the fixed number of the living room and D means the fixed number of drawing room. $\epsilon$, $\epsilon'$, $\epsilon''$represents the error terms for each building type. The whole linear equation can be separately found in Equation 2/Equation 3/Equation 4

$$Y5 = \beta_0^{(1)} + \beta_1^{(1)}X + \beta_2^{(1)}L + \beta_3^{(1)}D + \epsilon^{(1)} \tag{5}$$

$$Y6 = \beta_0^{(2)} + \beta_1^{(2)}X + \beta_2^{(2)}L + \beta_3^{(2)}D + \epsilon^{(2)} \tag{6}$$

$$Y7 = \beta_0^{(3)} + \beta_1^{(3)}X + \beta_2^{(3)}L + \beta_3^{(3)}D + \epsilon^{(3)} \tag{7}$$

The third model is similar to the second one and is also a Multiple linear regression. This model studies the effects of different Beijing housing prices (Price) on the two variables of Beijing center distance (dif_cor) and building structure (buildingStructure). In this model, I also added the number of Living rooms (livingRoom) and Drawing room (drawingRoom) as fixed variables to further increase the model accuracy. $Y_5$, $Y_6$, $Y_7$ represent the average price by the square of mixed, brick and concrete, and steel-concrete composite materials respectively. Units are consistent with other models. $\beta_0^{(i)}$ represents the intercept coefficient for building structure I such that i is equal to one of 2, 4, and 6, which is the average price by the square of three different building structures when the distance between the house and the center of Beijing is 0. $\beta_1^{(i)}$, $\beta_2^{(i)}$, $\beta_3^{(i)}$are the coefficients for the variables 'dif_cor, "livingRoom', and 'drawingRoom'respectively, for building structure i. X, L, and D all have the same as above. $\epsilon^{(i)}$ denotes the error term for building structure i. The whole linear equation can be separately found in Equation 5/Equation 6/Equation 7

## Features

What I am interested in in the Model section is the relationship between Beijing's housing prices and geographical location, building type, and building structure, and how they are transformed into different housing prices through coefficients in a linear regression equation. But for building type (buildingType), only three of the four types exist in the randomly

filtered data. There is no observation of the building type as the bungalow. This is because the bungalow is considered to be an Indian product and was popularized in the United States and other places rather than in China. (Mattson 1981) Correspondingly, for the building structure (buildingStructure) in the data set. Only half of the 6 species were collected in the sample. The reason behind this is that although wood materials such as mass timber have a high level of reducing carbon traces in nature, the solidity and non-flammability of reinforced concrete still dominate the field of building materials. (Barber 2018) For the features of these two variables, the establishment of the model becomes more representative for the situation of Beijing.

## Model Concerns

The most important factors in modeling and analyzing these relationships depend on the amount and authenticity of the housing information in the database. Since Kaggle does not have any restrictions on data extraction, I can extract the entire database, which ensures that the amount of data used to create the model meets the standard while reducing the variance of each house's data.

Unfortunately, there are loopholes in the authenticity of the data. Specifically, as mentioned in the Appendix, when using an influence plot to diagnose the model, it will be shown that some data have unreasonable data manifestations in the price variable. This means that I need to delete some data to ensure the accuracy of the entire linear regression equation. However, with data deletion, the overall data volume cannot meet the requirements mentioned above. This would indicate a lack of meaningfulness of the housing information in the data and reduce the credibility of the equation. These three models should benefit from a larger period in the data set, which means an increase in the amount of data that can be used to create models and represent increase in the overall data volume.

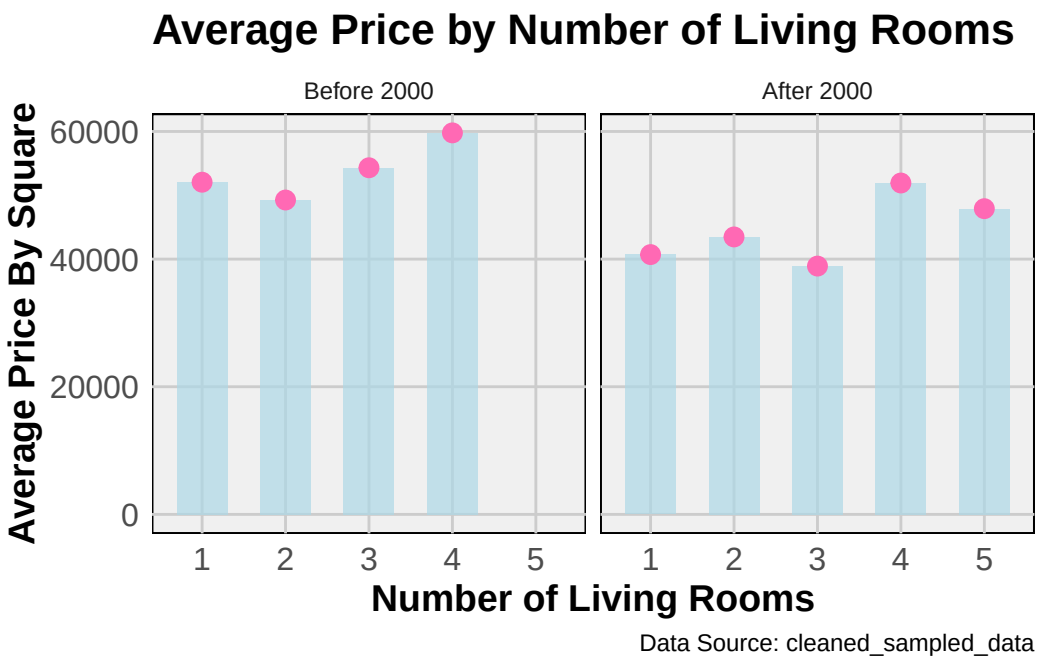



Figure 2

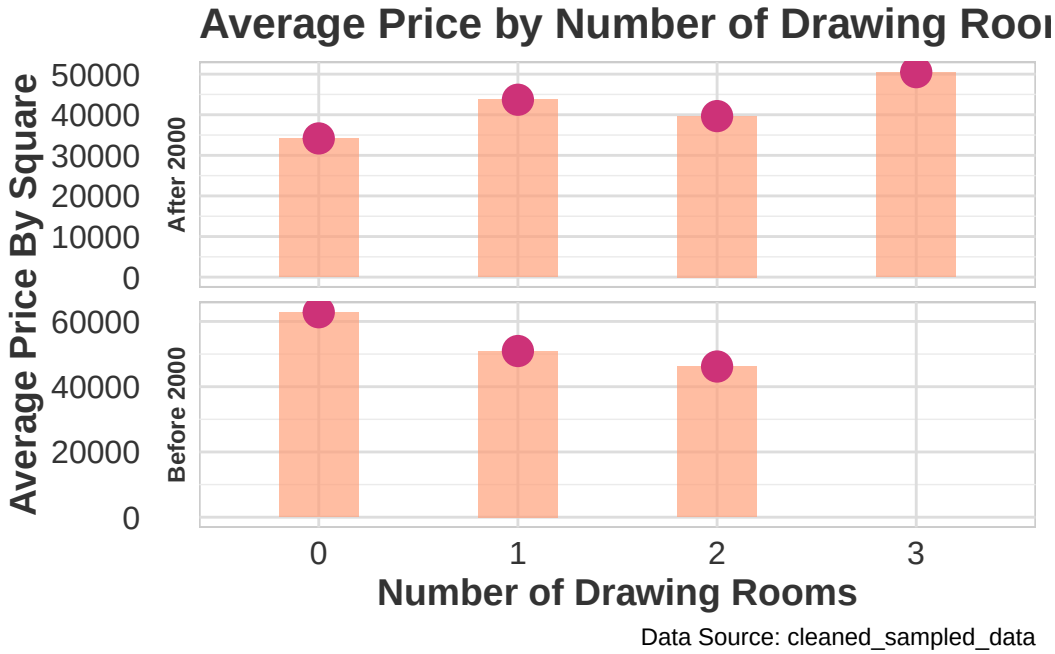



Figure 3

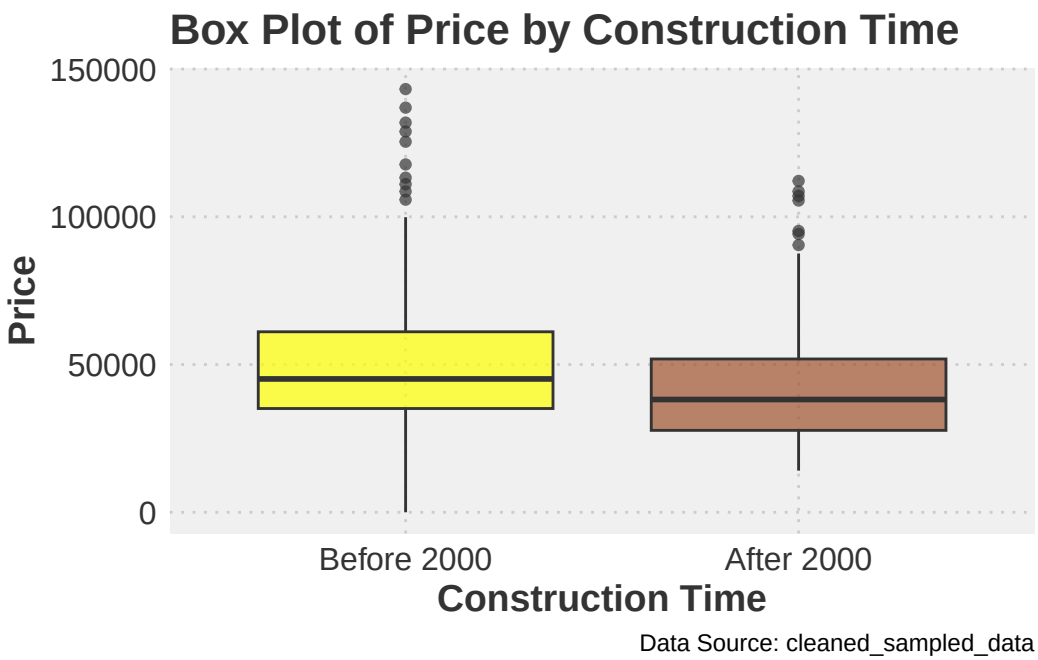



Figure 4


Figure 5

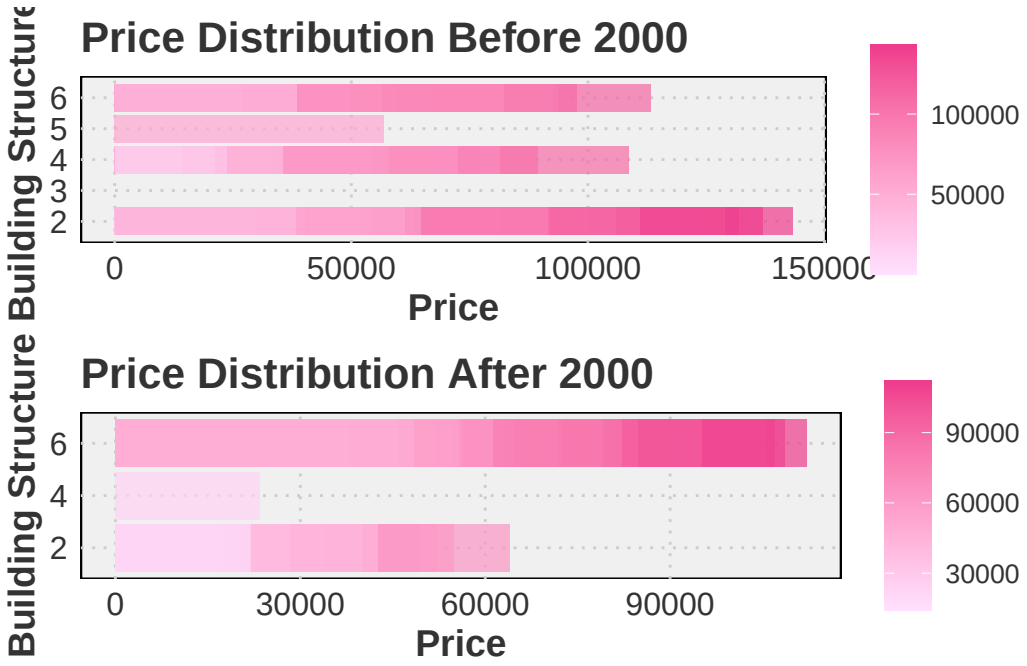



Figure 6

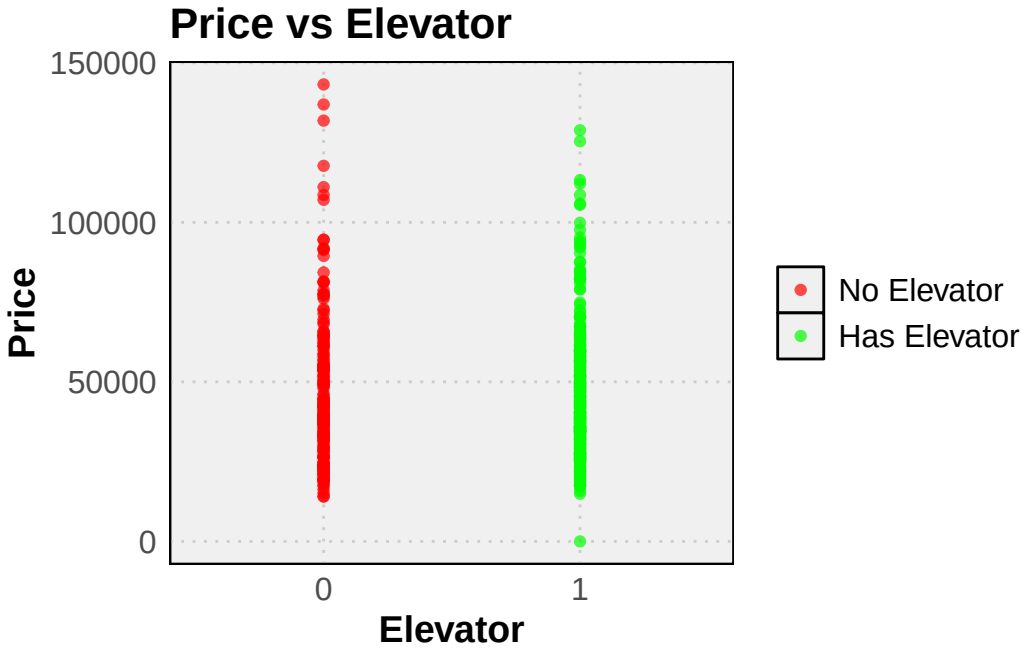



Figure 7

## Results

### LivingRoom and DrawingRoom & Price Interaction

### Construction Time & Price Interaction

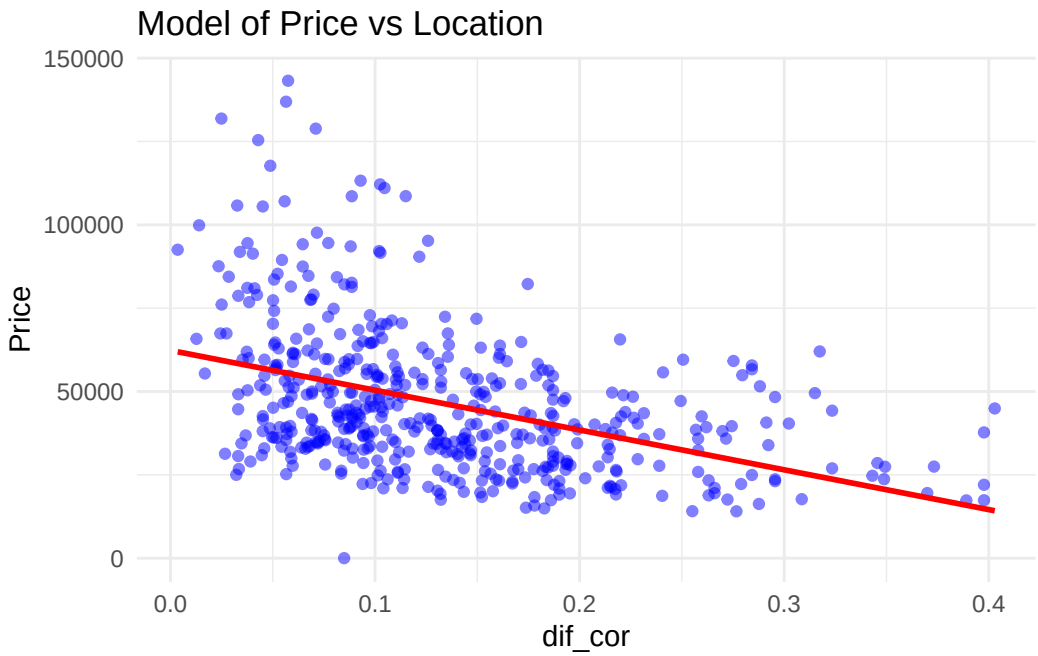
### Building Type & Price Interaction

### Building Structure & Price Interaction

### Elevator & Price Interaction

## Discussion

### Data and Model Findings



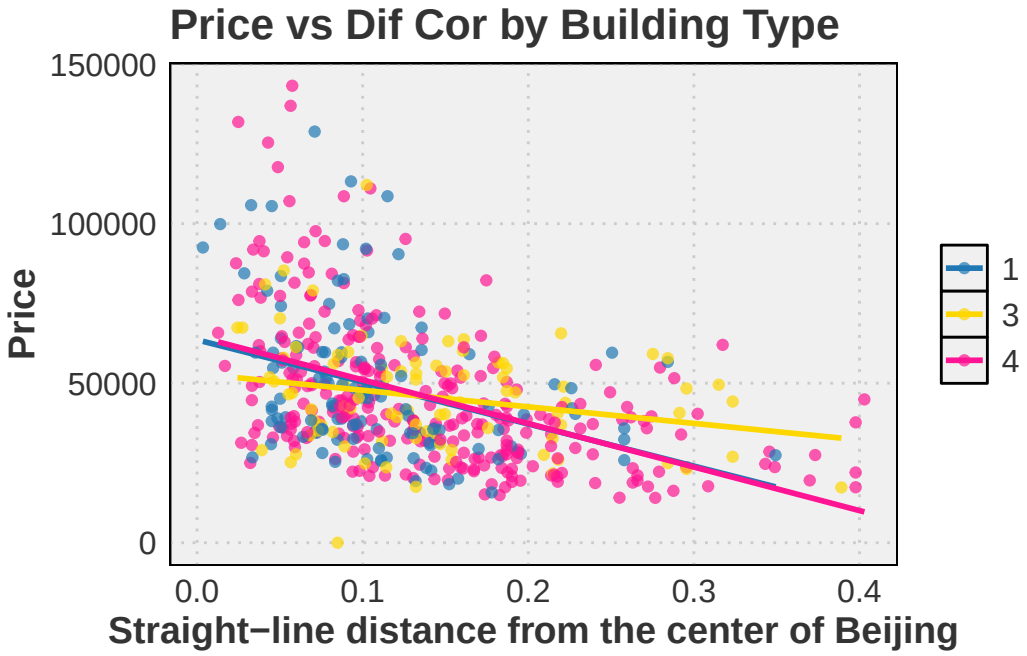



Figure 8: Prices with Different Building types

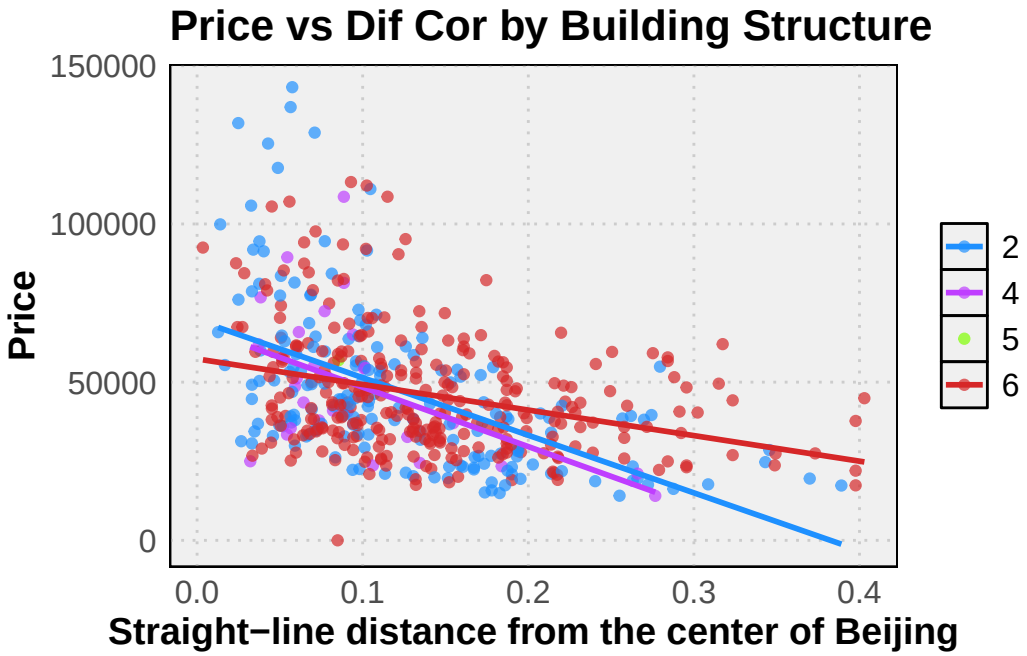



Figure 9: Prices with Different Building Structure

## Bias and Weakness

The source of the original data set is Lianjia Company, which is a representative real estate brokerage platform in China (Zhang et al. 2021). However, since Lianjia does not have professional certification in statistics, there are inevitably some inherent biases in the data set. I have no way to prove that Lianjia Company has fully provided all existing data. Further bias exists in the authenticity of the data. To be more specific, because real estate economics companies need to achieve certain performance, company personnel may hide many failure cases or fabricate some unreal success cases. Data recording may also be biased due to equipment failure or errors. These may affect the shape of our distribution

## Next Steps

# Appendix

## Diagnosing model

```
Call:
lm(formula = price ~ dif_cor, data = cleaned_sampled_data)

Residuals:
   Min     1Q Median     3Q    Max
-52193 -14260  -3944   8901  87755

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    62330       1774   35.14   <2e-16 ***
dif_cor      -119392      11557  -10.33   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 19820 on 493 degrees of freedom
Multiple R-squared:  0.178, Adjusted R-squared:  0.1763
F-statistic: 106.7 on 1 and 493 DF,  p-value: < 2.2e-16
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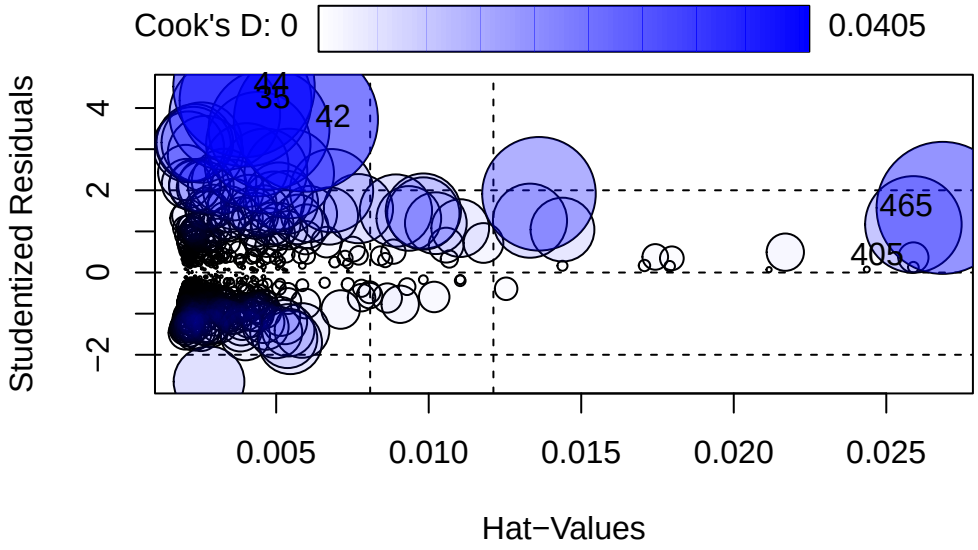


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      StudRes         Hat       CookD
35  4.1810941 0.003996377 0.033937031
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42  3.7173550 0.005974810 0.040477791
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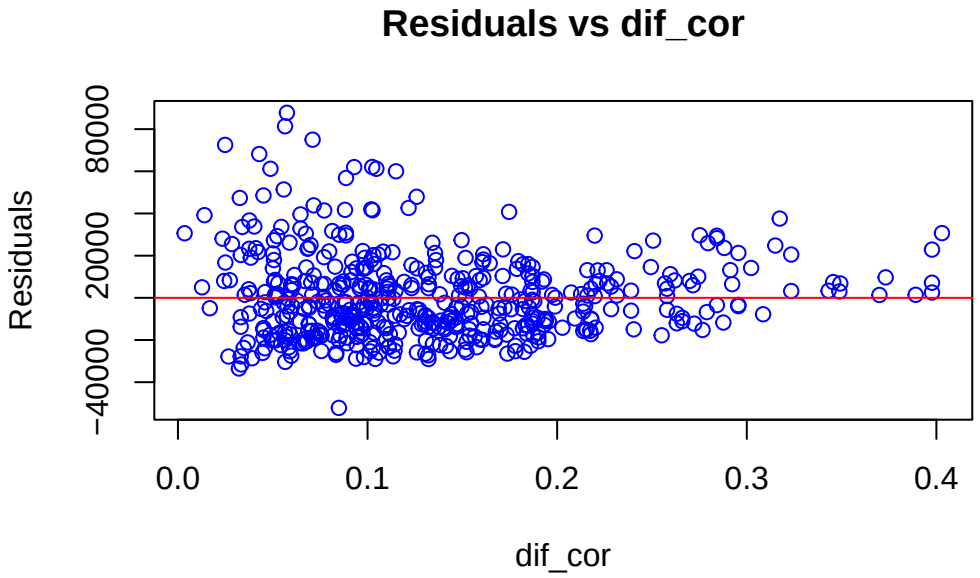


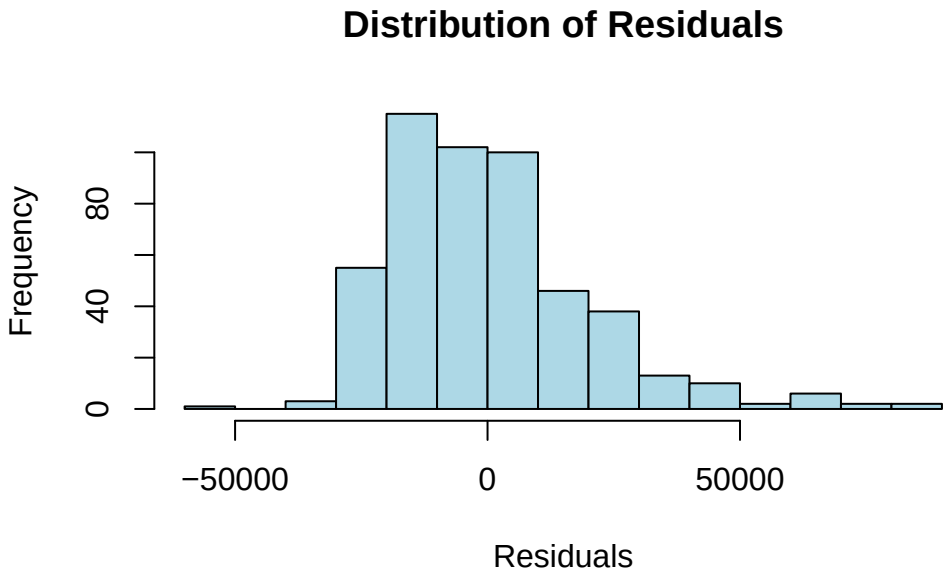

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