

# **Beauty In Distance: How Distance Affects Housing Prices around Foreign-owned Private Hospitals in Shanghai**

**ECON2901AS01 Final Report**

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# 1 INTRODUCTION

## 1.1 Background

Since 2025, the Chinese government has introduced new policies on foreign-owned private hospitals, allowing foreign capital to establish medical institutions independently in Mainland China (China Daily, 2025). This indicates a gradual transformation in the medical industry in Mainland China. According to a report by Zhiyan (2024), there is a continuously expanding trend in the market size of high-end medical services, with private medical institutions taking 65% of the market.

Meanwhile, the real estate industry in Mainland China is experiencing a changing point. Although it experienced overall depression during COVID-19, the market is now gradually recovering. Wu et al. (2024) pointed out in their research report on housing demand that a rise has been witnessed in Mainland Chinese consumers' willingness to purchase housing in 2024.

In order to dive deeper into the topic, a typical city, Shanghai, has been selected to develop further discussion. This metropolis has shown an active market and considerable purchasing power, which is perfectly aligned with the target consumer profile of foreign-owned private healthcare. According to Gotohui (2025), the average housing price in Shanghai reached the 2<sup>nd</sup> highest in Mainland China. Moreover, income per capita and consumption per capita in Shanghai both reached the top among Mainland cities in 2023 (Gotohui, n.d.).

## 1.2 Motivation

This study stands as the pioneer in exploring the relationship between the distances to private healthcare and housing prices in Shanghai. It is motivated by the aim to bridge the existing knowledge gap by developing an insight into the influence of foreign-owned private healthcare in Mainland China. A thorough understanding of the relationship between medical services and housing prices is pivotal in designing effective strategies in real estate. In addition, the findings can also provide practical guidance in investment for commercial housing consumers, and can therefore promote housing equity and reduce irrational investment.

# 2 LITERATURE REVIEW

## 2.1 Theory Basis

### 2.1.1 The Importance of Housing Prices and Medical Services

Among various factors that influence people's well-being, housing price is of obvious significance (Cui et al., 2018). It plays an important role that often involves large amounts of expenditure and affects

quality of life on an everyday basis. Meanwhile, Chinese people have been paying close attention to housing prices for a long time (Chen et al., 2021).

Another active factor towards well-being is medical services. 2 dimensions are usually adopted when evaluating medical services. Firstly, people show obvious concern towards the quality of medical services, asking for more outstanding medical staff and more advanced equipment (Mosadeghrad, 2014). Secondly, accessibility is often taken into consideration, since it is a crucial indicator for equality of health. Better health conditions are easier to achieve with relatively higher accessibility (Kelly et al., 2016)

### *2.1.2 Previous Studies Related to the Relationship between Healthcare and Housing Prices*

As Zeng and Zhou (2017) pointed out in their study, the housing price is generally negatively correlated with the distance to medical services. Moreover, we have also noticed a study done by Peng and Chiang in 2015, introducing the concept of “semi-obnoxious facilities” to this topic. They examined the housing data in Taipei, and the result showed that housing prices are not linearly related to distances to healthcare. On one hand, easy access to healthcare acts as a significant factor in considering the convenience of a house, leading to relatively lower prices for further houses. On the other hand, concerns have been raised since medical facilities might bring nuisance, such as the risk of infection and traffic jams.

Furthermore, Li and Liang (2022) conducted research and mentioned the differences between the impact of several kinds of medical services. General hospitals are mostly more effective when influencing housing prices than clinics.

In addition, the studies on Class 3A public hospitals provide sufficient evidence of the situation. These hospitals are widely considered as the top tier of healthcare in Mainland China, resulting in a “Siphon Effect”. People hold distinct preferences towards these hospitals and therefore enhance the gathering of resources. In this way, the quality of medical services from Class 3A public hospitals gets into a positive circulation, leading to better evaluation of a house when considering its accessibility. As a result, the study done by Shen and Li in 2021 and the study done by Lv and Zhao in 2018 both proved that Class 3A hospitals have the strongest influence on surrounding housing prices.

## *2.2 Research Objective and Research Gap*

Although various studies have been done to investigate the impact of public hospitals on housing prices, we have noticed a similar “Siphon Effect” in this field, as the studies are mostly focused on Class 3A hospitals. Limited previous research on private healthcare has basically focused on specialist clinics, which have neglected the market of private general medical services. This might be due to a relatively smaller market size of private healthcare in Mainland China. Given the research background

and current situation of this topic, our study intends to answer how the housing prices are influenced by their distances from foreign-owned private healthcare facilities by investigating the situation in Shanghai. This study can address the research gap and contribute to the comprehensiveness of understanding the housing market.

### 3 DATA

#### 3.1 Data Collection and Descriptive Statistics

This study examines the relationship between housing prices of properties around foreign-owned private hospitals and the distance to hospitals in Shanghai. Therefore, we centered on hospitals respectively by collecting the housing prices of communities within a certain distance in several distance segments as the main data. In addition to this, we also collected data on some relevant control variables.

##### 3.1.1 Foreign-owned hospitals in Shanghai

According to the Shanghai Municipal Health Commission (2024), there are twenty-nine foreign-owned private hospitals in Shanghai. To attenuate the differences in the attractiveness of different hospitals, we select only general hospitals. Additionally, we removed hospitals with only sparse communities to reduce the error in the results. Finally, we selected 18 hospitals, as shown in the table below.

**Table 1:** Hospitals Selected

No.	Name	Location
1	Artemed Hospital	Pudong New Area
2	Parkway Shanghai Hospital	Minhang District
3	Pantheon Clinic	Minhang District
4	Dracaena Healthcare, Chengle Clinic	Changning District
5	Deltahealth Hospital	Qingpu District
6	Shanghai East International Medical Center	Pudong New Area
7	Guang-Ci Memorial Hospital	Huangpu District
8	Landseed Hospital	Xuhui District
9	Shanghai United Family Pudong Hospital	Pudong New Area
10	Shanghai United Family Changning Hospital	Changning District
11	Shanghai United Family Changning Hospital	Jingan District
12	Jiahui Health	Xuhui District
13	Shanghai Jiajing Clinic	Jingan District

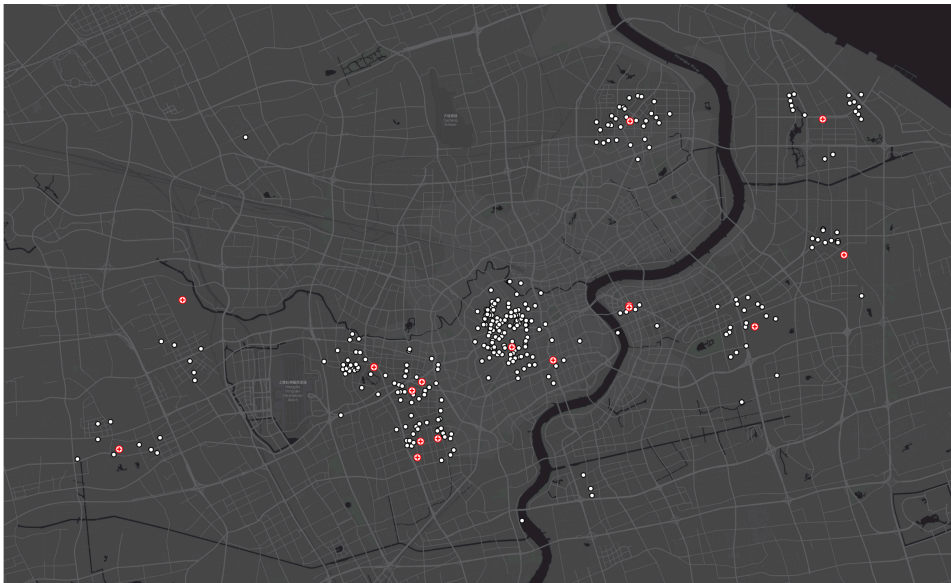
**Table 1 (Continued): Hospitals Selected**

14	Shanghai Jiashang Clinic	Yangpu District
15	Raffles Medical Shanghai Hospital	Pudong New Area
16	MJ Health Care	Changning District
17	GHC Global health Care	Jingan District
18	Shanghai Ruidong Hospital	Pudong New Area

### 3.1.2 Communities (Housing price & Distance)

For communities, we focus on collecting housing prices and the distance to the nearest hospitals. Regarding housing prices, we collect data from the *Beike* website, one of China's leading digital renting platforms (Zhang & Yao, 2022). We chose the price of a second-hand property because it is more responsive to the impact of surrounding facilities and is relatively stable. Moreover, we choose the average price of one community rather than the price of a single house to better exclude the influence of individual complex factors, such as the orientation of the house, feng shui, and other influences. Regarding the distance data, we collect it from *AMAP (Gaode)*. We use the linear distance from the communities to the nearest hospital as the distance variable. Referring to other literature, we delineate the scope as being centered on the hospital and collecting communities' data within two kilometers, which is an effective radius of impact for most public facilities (Si & Shi, 2013). Furthermore, according to the Shanghai "15-minute community life circle" Action, which means that distances within 1km are facilitated, we refine the distance range into two segments of 0-1km and 1-2 km, and we search for the same amount of data with these two segments (Shanghai Urban Planning and Natural Resources Bureau, n.d.).

Figure 1 is the map of hospitals and communities created by QGIS. In this picture, red dots are the hospitals, and white dots represent communities.

**Figure 1: Map of Hospitals and Communities**

### 3.1.3 Other Variables

Apart from the independent variable distance, which we mainly focus on, our study also considers other important factors likely to influence the house's value, including housing characteristics, neighborhood characteristics, and medical-related variables (Peng & Chiang, 2015). For housing itself, we introduce 'Age of House,' 'Greening rate,' and 'Plot ratio' as control variables. Regarding the neighborhood characteristics, we examine various factors, such as transport, dining, leisure, and shopping. After specific testing, we ultimately chose 'MRT (Metro)' and 'Commercial Complex', which are more significant. Moreover, since our study is on foreign-owned private hospitals, we also consider the degree of healthcare demand and whether there is competition with public hospitals. The following table shows all the variables involved in our study.

**Table 2:** Variables Involved

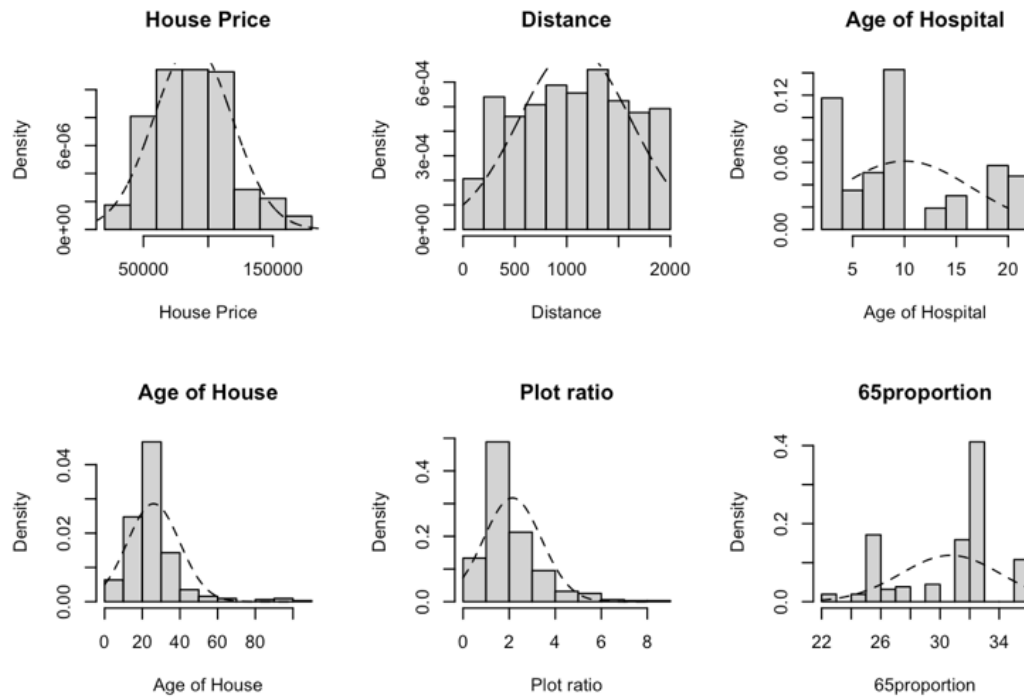
Variable name	Description	Type
Housing Price	Average second-hand housing prices (yuan) in March provided by <i>Beike</i>	Continuous variable
Distance	Linear distance (meter) from communities to the nearest foreign-owned private hospital provided by <i>AMAP</i>	Continuous variable
Age of Hospital	Hospital's founding year to 2025	Continuous variable
Age of House	Year of Communities' earliest houses to now	Continuous variable
Green	Greening rate of communities (%)	Continuous variable
Plot.ratio	Average Plot ratio of communities	Continuous variable
X65proportion	Percentage of population over 65 in the district	Continuous variable
Public_hospital	Yes=1, if there is a public hospital near the communities (<=2km)	Dummy variables
MRT	Yes=1, if there is a Metro station near the communities (<=2km)	Dummy variables
Commercial_Complex	Yes=1, if there is a Commercial Complex near the communities (<=2km)	Dummy variables

### 3.2 Descriptive Statistics

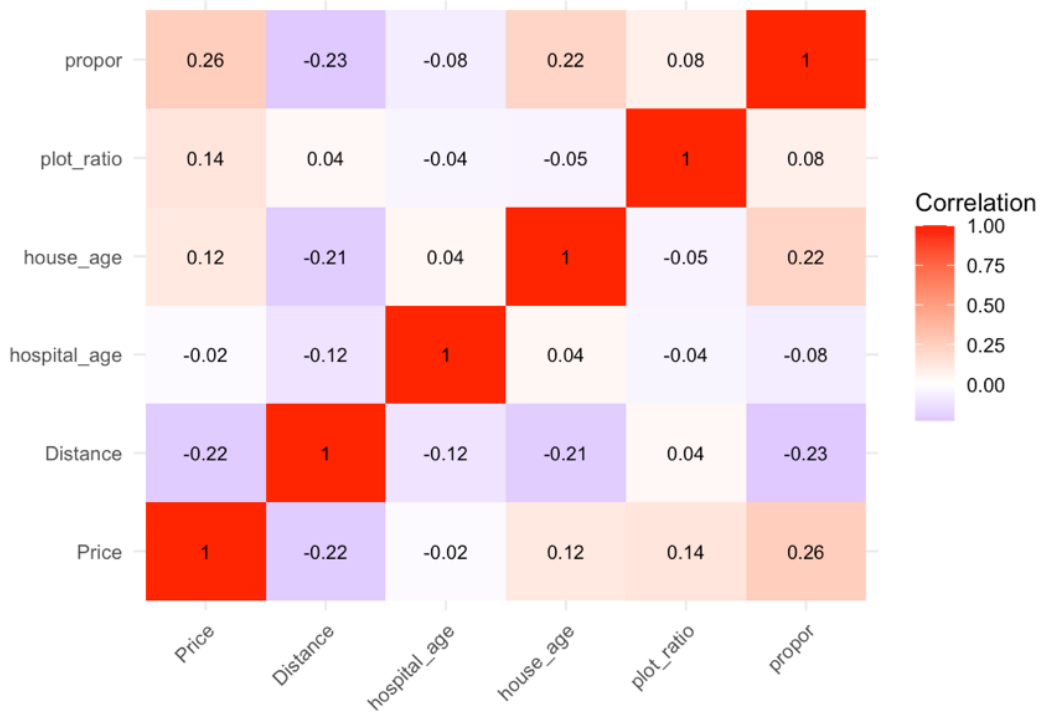
The following table is a statistical description of numerical variables in our study. There are a total of 315 observations. The average distance is 1078m, which is close to 1000m, indicating that we successfully selected a similar number of communities on two distance segments.

**Table 3:** Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
House price	315	88261.575	30143.996	30681	173935
Distance	315	1078.524	538.998	54	2000
Age of Hospital	315	10.022	6.53	2	22
Age of House	315	25.997	13.944	2	101
Green	314	.456	1.959	.05	35
Plot ratio	315	2.147	1.256	.21	9
X65proportion	315	30.718	3.356	22.64	35.1



**Figure 2:** Density Histogram of Numeric Variables



**Figure 3:** Correlation Plot of Numeric Variables

From Figure 2, we can see that housing prices and distances are, to some extent, normally distributed. Moreover, from Figure 3, we can predict the direction of the influencing price factors. The age of houses, plot ratio, and 65 proportion are positively related to housing price, while the distance and age of hospitals are negatively related to the price.

## 4 METHODOLOGY & RESULTS

### 4.1 Regression Analysis

#### 4.1.1 Model Specification

According to the variables explained above, we choose *Price* as our dependent variable, 9 related variables (*Distance*, *Age\_of\_hospital*, *Age\_of\_house*, *Green*, *Plot.Ratio*, *X65proportion*, *Public\_hospital*, *Commercial\_complex*, *MRT*) as our independent variables. The research studies the relationship between *Price* and *Distance*, so we mainly focus on the coefficient (Beta) and standard deviation (SE) of the variable *Distance*. Other variables are included to avoid omitted variable bias. To construct a suitable model, we consider choosing model types and comparing different model specifications.

#### a) Choosing Model Types

Different model types (function forms) can significantly affect the model's goodness-of-fit. Four typical types are considered: linear, linear-log (some of the independent variables are in logarithm forms), log-linear (only the dependent variables are in logarithm forms), and log-log (the dependent and

some independent variables are in logarithm forms). Comparatively, the log-linear function demonstrates higher significance and fitness. Transforming the dependent variable Price into logarithm form, the final function form is:

$$\ln(\text{Price}) = \beta_0 + \beta_1 \times \text{Distance} + \beta_2 \times \text{Age\_of\_hospital} + \beta_3 \times \text{Age\_of\_house} \\ + \beta_4 \times \text{Green} + \beta_5 \times \text{Plot.Ratio} + \beta_6 \times \text{X65proportion} \\ + \beta_7 \times \text{Public\_hospital} + \beta_8 \times \text{Commercial\_complex} + \beta_9 \times \text{MRT}$$

b) Model Specifications

**Table 4** Regression Results of OLS Regression Model Under Different Specifications

(lnprice)	Model 1		Model 2		Model 3	
Regressors	Beta <sup>1</sup>	SE <sup>2</sup>	Beta	SE	Beta	SE
Distance	-0.000152*	0.000	-0.000098***	0.000	-0.000074***	0.000
Age_of_hospital			0.001057	0.003	0.001673	0.003
Age_of_house			0.001880	0.001	0.001089	0.001
Green			-0.000683	0.010	-0.001105	0.010
Plot.Ratio			0.038182**	0.015	0.027519*	0.015
X65proportion			0.030414***	0.006	0.026119***	0.006
Public_hospital					0.084057*	0.046
Commercial_complex					0.095523*	0.049
MRT						
No.Obs.	315		314		313	
Adjusted R <sup>2</sup>	0.048		0.144		0.161	
p-value	<0.01		<0.01		<0.01	
AIC	242		209		205	

<sup>1</sup> \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 only

<sup>2</sup> All SEs are rounded to the third decimal.

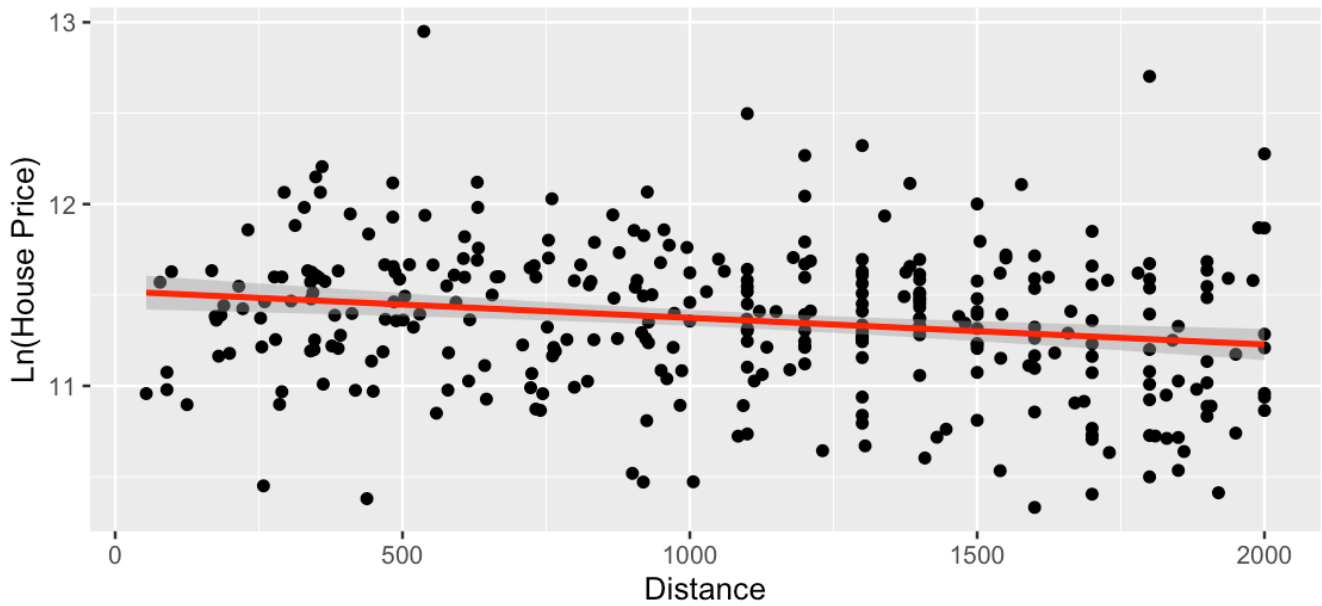
**Table 4 (Continued)** Regression Results of OLS Regression Model Under Different Specifications

Model 4		Model 5		Model 6	
Beta	SE	Beta	SE	Beta	SE
-0.000104***	0.000	-0.000098***	0.000	-0.000095***	0.000
0.003783	0.003	0.003943	0.003	0.004000	0.003
0.000971	0.001	0.000670	0.001	0.000574	0.001
-0.002250	0.009	-0.002327	0.009	-0.002398	0.009
0.027127*	0.015	0.026399*	0.015	0.024376	0.015
0.023771***	0.006	0.021947***	0.006	0.021101***	0.006
				0.073878*	0.045
0.044869	0.048			0.037714	0.048
0.269290***	0.052	0.273403***	0.050	0.265480***	0.052
313		314		313	
0.221		0.226		0.226	
<0.01		<0.01		<0.01	
182		180		181	

<sup>1</sup> \*p<0.1; \*\*p<0.05; \*\*\*p<0.01 only

<sup>2</sup> All SEs are rounded to the third decimal.

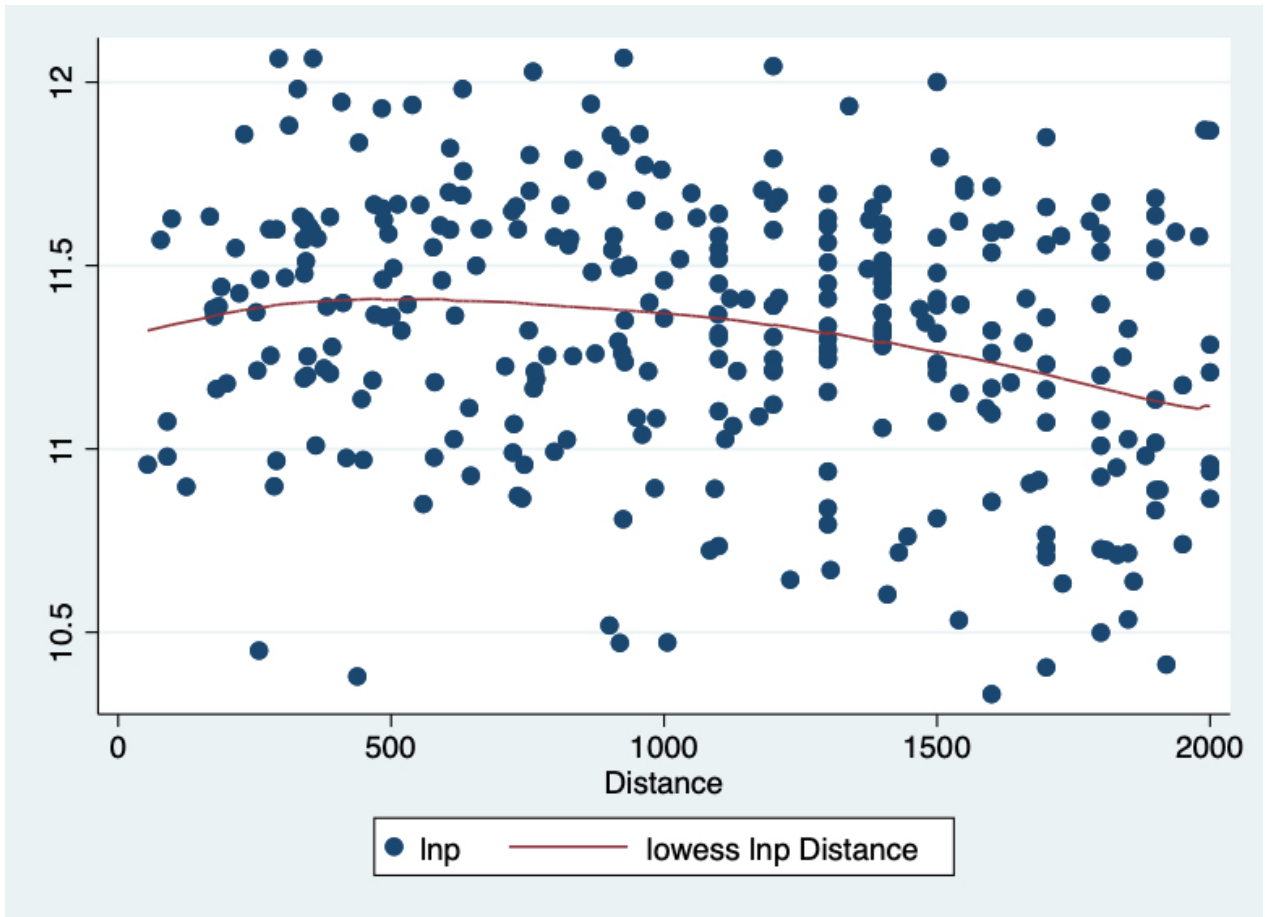
Table 4 presents the global regression results under different model specifications. The main variable concerned, *Distance*, should be significant ( $p < 0.01$ ), and the Adjusted R square should be higher. In model 1, only *Distance* is included, and the coefficient is only significant at the 10% level ( $p < 0.1$ ). Comparatively, in model 6, all 9 independent variables are included, so that the possibility of having omitted variable bias is the lowest. Also, the coefficient of *Distance* is significant at the 1% level ( $p < 0.01$ ), and the adjusted R-squared is the highest among all specifications. All coefficients of *Distance* are not significantly different, so beta can be considered as a robust estimator.



**Figure 4:** The global OLS Regression Curve in a Scatterplot (Focusing on *Distance*)

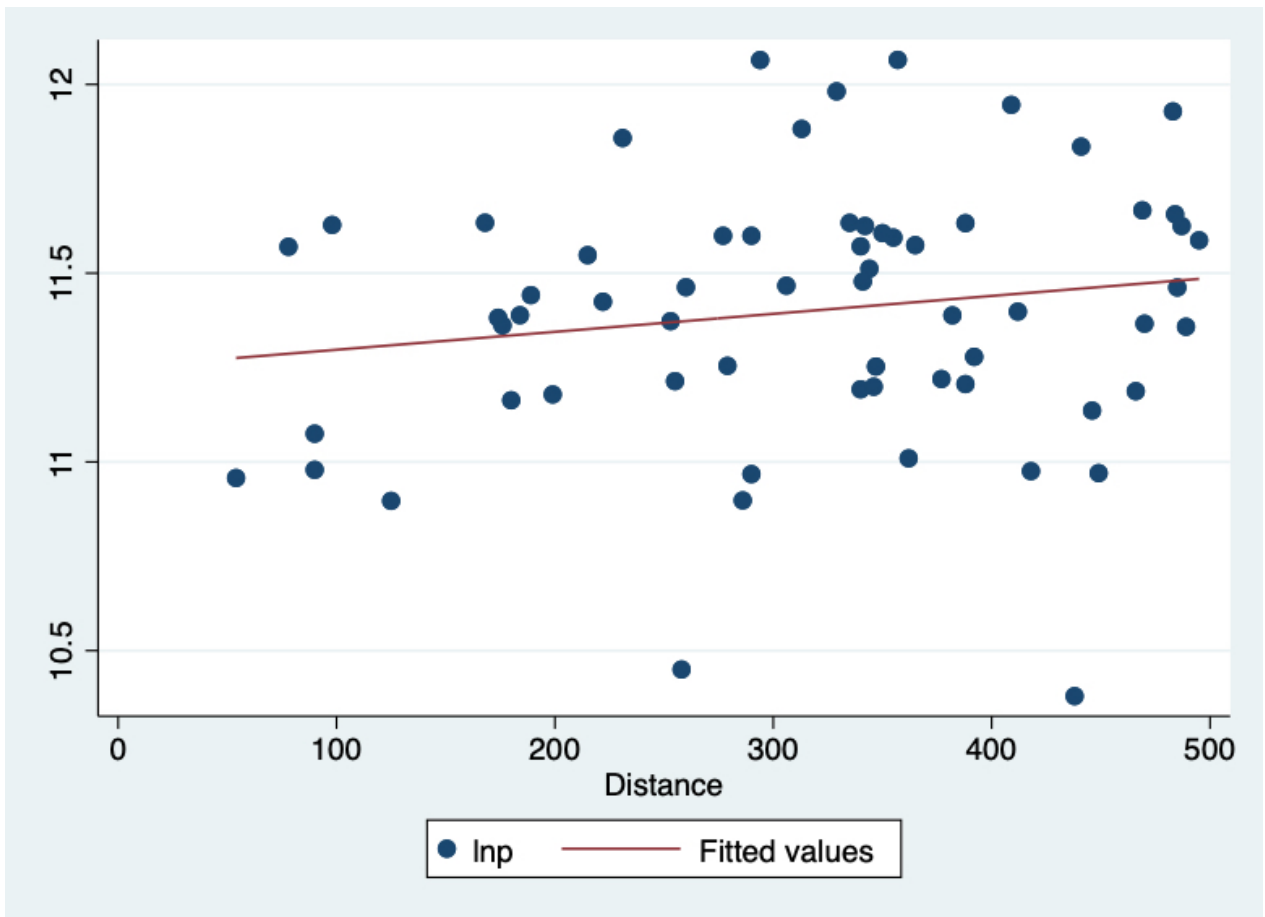
#### 4.1.2 LOWESS (Locally Weighted Regression) Curve & Piecewise Regression

LOWESS (Locally Weighted Regression) is a method for generating a smooth curve in a scatterplot, demonstrating the trends of the regression curve more specifically (Wilkinson, 1979). All dots are divided into fractions and regressed under OLS assumptions locally to form a smooth curve. In Stata, a LOWESS curve can be generated directly in a scatterplot using the command *lowess*.

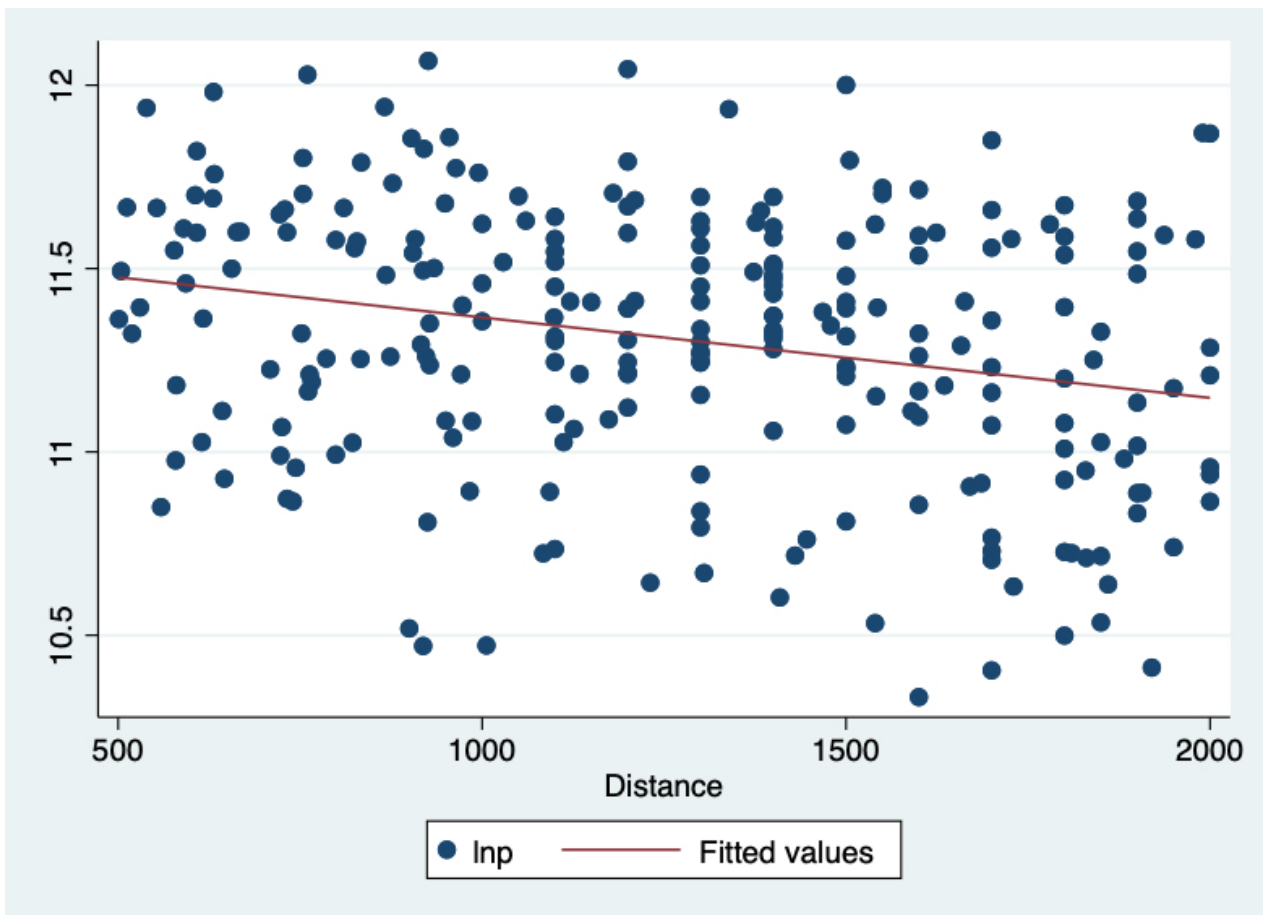


**Figure 5:** The LOWESS Curve in a Scatterplot (Focusing on *Distance*)

This LOWESS curve demonstrates an increasing-decreasing trend on *Distance*, and the turning point is roughly at *Distance*=500 meters. To further analyze the relationship between  $\ln(\text{Price})$  and *Distance*, this study divided the data into two fractions:  $0 < \text{Distance} < 500\text{m}$  and  $500\text{m} < \text{Distance} < 2000\text{m}$ . Two separate regressions are conducted in Stata using the command *if*. As shown in Figure 6 and Figure 7, when  $0 < \text{Distance} < 500\text{m}$ , the slope is positive ( $\beta > 0$ ), and *Price* increases as *Distance* increases. When  $500\text{m} < \text{Distance} < 2000\text{m}$ , the slope is negative ( $\beta < 0$ ), and *Price* decreases as *Distance* increases.



**Figure 6:** Piecewise OLS Regression Curve ( $0 < \text{Distance} < 500\text{m}$ )



**Figure 7:** Piecewise OLS Regression Curve ( $500\text{m} < \text{Distance} < 2000\text{m}$ )

## 4.2 Analysis of Regression Results

This study mainly focuses on the correlation between *Price* and *Distance*, rather than constructing a best-fitted model. In Table 4, the robust coefficient of *Distance* is negative, and the global regression curve has a negative slope. It suggests that holding other factors constant, when *Distance* increases, housing price generally decreases. This result is consistent with the suggestion in the paper written by Zeng & Zhou (2017). The LOWESS analysis demonstrated an increasing-decreasing trend with the turning point at *Distance*=500m, which supports the semi-obnoxious assumption (Peng & Chiang, 2015): Because of the semi-obnoxious attribute of the hospitals, property buyers prefer longer distance (to the nearest hospital) within 500 meters, while they prefer shorter distance beyond 500 meters. To further reveal the reasons, this study analyzed the supply-demand relationship and consumer preference at the microeconomic level.

## 5 MICROECONOMIC ANALYSIS

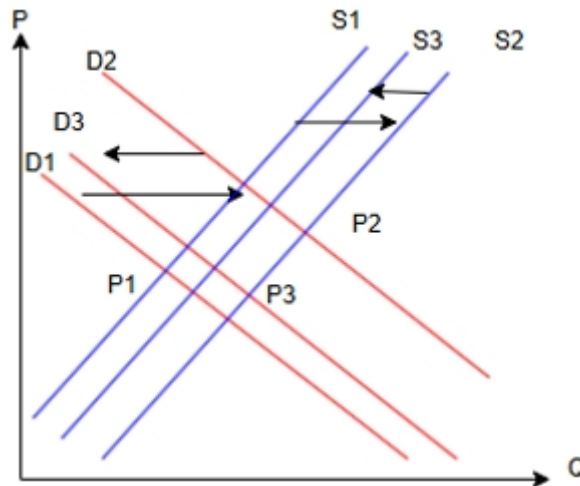
### 5.1 Elasticity Analysis

The price elasticity of distance is calculated as:

$$Ed = \frac{\% \Delta \text{HousePrice}}{\% \Delta \text{Distance}}$$

Empirical data reveal a threshold effect at 500 meters. When *Distance*>500 m, the average elasticity is positive ( $Ed=0.253>0$ ), indicating that greater distance correlates with higher housing prices. Conversely, for *Distance*<500 m, elasticity turns negative ( $Ed=-0.352<0$ ), implying that proximity reduces prices.

### 5.2 Demand and Supply Analysis



**Figure 8:** Demand and Supply Curve

### 5.2.1 Demand-Side Dynamics

Consumer preferences drive this dichotomy. At  $Distance < 500$  m, households perceive hospitals as disamenities due to noise, traffic congestion, and disease exposure risks (Si & Shi, 2013). This reduces demand, shifting the demand curve leftward ( $D1 \rightarrow D2$ ). When  $Distance > 500$  m, medical accessibility dominates preferences ( $D2 \rightarrow D3$ ). It has been demonstrated that the greater the distance to health care services, the less accessible these services are to residents, which in turn has a reducing effect on demand (Tao & Shen, 2018).

### 5.2.2 Supply-Side Dynamics

Land near hospitals is in short supply, so prices show a scarcity premium, raising development costs. At distances less than 500 m, limited land supply restricts the supply of housing and supply decreases ( $S1 \rightarrow S2$ ). At distances greater than 500 m, the supply of land increases, but supply is inversely proportional to demand, and a demand reduction will also result in a reduction in supply (Gale, 1995). When consumer demand for housing weakens, developers will reduce construction activity. The supply curve also shifts to the left ( $S2 \rightarrow S3$ ).

## 6 CONCLUSION

Our study uses a hedonic price model to analyze the relationship between housing prices and distance to advanced health services provided by foreign-owned private hospitals in Shanghai. We adopt a multiple regression model and comprehensively consider three categories of factors influencing prices: housing characteristics, neighborhood characteristics, and medical factors. The regression results show that distance is negatively correlated with housing prices, which means the further the communities are from the hospitals, the lower the average housing prices. Considering the special attributes of the hospital, which bring both convenience and potential dangers, our study further examines the locally weighted regression. Within 500 meters, environmental factors are perhaps more important, with a positive correlation between price and distance, while beyond 500 meters, location factors are more important, with a negative correlation between price and distance. This provides strong evidence that foreign-owned private hospitals in Shanghai also have semi-obnoxious effects.

In terms of urban planning policy, a new foreign-owned private hospital should be allocated in a populated area to guarantee customer flow. However, based on our study, spatial distance must be maintained from the nearby communities, and spatial barriers must be set to reduce negative externalities.

## 7 LIMITATION

### *7.1 Threats to Internal Validity*

This study is subject to several limitations that warrant acknowledgement. Regarding internal validity, first, the potential for omitted variable bias persists despite our rigorous model specification. Although we controlled observable confounders, unmeasured variables correlated with both independent and dependent variables may still affect the result, becoming inconsistent. Secondly, the missing data could inflict the sample selection bias, particularly given the non-random nature of data incompleteness (Stock & Watson, 2020).

### *7.2 Threats to External Validity*

In terms of external validity, two critical constraints emerge. The analysis lacks consumer group stratification (e.g., by age cohort or income bracket), thereby constraining the identification of heterogeneous treatment effects across population segments; a methodological limitation substantiated by prior empirical findings demonstrating that non-classified models tend to overestimate aggregate effects (Ailawadi & Gedenk, 2001). Furthermore, the exclusive focus on Shanghai's metropolitan context restricts generalizability given China's significant regional disparities in consumption patterns from 2008 to 2020 (Xing & Ye, 2023). Urban-rural differences and regional economic variations likely moderate the observed relationships. Future research could expand the sample diversity and validate the generalizability of this study by studying other cities.

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