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RESEARCH

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Non-linear distance decay effects of clean energy facilities in housing rental and sale markets: Evidence from hydrogen refueling stations

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Abstract
While promoting green and low-carbon transition, clean energy facilities also have externalities, which may lead to opposition and economic losses. There is evidence that the impact of facilities decreases with distance, but existing research make strict assumption on its functional form. In this research work we explore the non-linear relationship between housing transaction prices and distances to the nearest facility without predefined functions combined with spatial smoothing in the hedonic pricing model by taking China as a case-study. We use the housing transaction data from 2015 to 2018 to estimate the distance decay of HRS (Hydrogen Refueling Station) in different regions in the rental and sale markets. The results show that the HRS has a significant negative impact on sale prices, while it has no significant impact on rental prices. In the sale market, for every 1% decrease in the distance, the house prices decrease by 6.62%, and the main impact distance is 3.5 km. In the eastern region, HRS has a significant impact on both rents and prices; in the central and western regions, there may be a positive impact on the rental market, but there is no significant impact in the northeastern region. Based on the empirical results, policy recommendations are given.

Keywords:
Clean energy facility; Hydrogen refueling station; Non-linear distance decay; Hedonic

1. Introduction

Clean energy usually tops the list of changes that can be implemented to massively cut carbon emissions and mitigate climate change. Clean energy can benefit the climate by displacing emissions from fossil-fueled electrical generating units (Buonocore et al., 2016)[1], reducing the GHG emissions of the manufacturing facilities (Zhai et al., 2011)[2], and changing the energy used for cooking. Moreover, clean energy can improve public health by reducing pollution (Haines et al.,2007)[3]. Two major sources of disease burden today from energy use are indoor and outdoor air pollutions (Holdren et al., 2000)[4]. The effect of urban air pollution on health in cities with populations over 100 000 is substantial with attributable annual mortality of about 0.8 million (WHO, 2002)[5]. Serious diseases like heart attacks and Asthma will be reduced due to reductions of NO_x and SO_x (Hosenuzzaman et al., 2015)[6].

Proper application of clean energy requires first the construction of clean energy facilities. To achieve the Paris Agreement goals, more and more clean energy facilities have been built across the world. Over 3 million installations of solar energy have been built across America, with 1 million being built in the last two years (DOE, 2022)[7]. In Europe, 17 GW of new wind capacity has been installed in 2021 and it is not even half of what the EU should build in order to be on track to deliver its 2030 goals (WindEurop, 2022)[8]. By the end of March 2022, China's installed capacity of solar power reached 320 GW and wind power capacity was 340 GW (NEA, 2022)[9].

However, clean energy facilities themselves may have a bad influence on the environment and health, which could lead to social welfare losses and new inequalities. It has been found that clean energy facilities may cause chronic accidents including leaks and safety incidents (Kiyotaka, 2017;[10] Park et al., 2021[11]), catastrophic accidents such as nuclear meltdowns (Lelieveld et al., 2012)[12], hydrogen refueling station explosions (Li et al., 2010)[13], dam breaches (Zhong et al., 2021)[14], aesthetic issues like noises (Merino-Martínez et al., 2021)[15] and visual impacts (Saidur, 2011)[16], animals death and habitats destruction (POST, 2006[17]; Saidur et al, 2011[18]).

The construction of clean energy facilities may result in a spatial shift of benefits, where nearby residents have to bear the environmental and health impacts, while residents in a larger geographic area may enjoy benefits. Negative externalities lead to the loss of welfare in the surrounding area (von Mollendorff and Welsch, 2015)[19], and also cause residents' opposition to the facilities, which hinders the construction of facilities in the local area (Van der Horst, 2017;[20] Huijts et al., 2012; Hoen et al,.2015[21]). Hedonic can capture changes in benefits by analyzing the impact of amenities on surrounding property prices (Rosen, 1974)[22]. But spatial heterogeneity has not received enough attention. The purpose of this study is to firstly determine the impact distance, secondly, within the impact distance, observe the change of the impact of facilities with distance, and thirdly, to observe the different impacts of facilities in various regions.

Current studies reflect the spatial heterogeneity mainly from two aspects. In the first category of study, spatial heterogeneity is shown as the impact buffer of the facilities (Dröes and Koster, 2016; Krekel and Zerrahn, 2017[23]; Haninger et al.,2017). Distance group regression (Dröes and Koster, 2016)[24] or relationship graph between housing prices and distances (Haninger et al.,2017)[25] is often the base structure for the main model. However, they only show the difference between the impact area and the non-impact area, with results at the average level, and cannot observe the difference within the impact buffer. In the second category of studies, distance can be seen as a key variable in the model. Meta-analysis results demonstrate statistically significant and intuitive influences of distance and other spatial factors on willingness to pay (Johnston et al., 2019)[26]. Distance decay has been found in different research fields. In ecological economics, distance decay is related to amenity (Łaszkiewicz et al., 2022)[27] or risk (Rajapaksa et al., 2017;[28] Bernstein et al.,2019[29]). In geography, distance decay is also called geographic discounting similar to the time value of money in economics, which suggests the people's preference to the "good" (Hannon, 1994)[30]. However, only a few studies focus on the energy facilities (Jarvis, 2021;[31] Zemo et al.,2019[32]), and clean energy facilities have been ignored, which is inconsistent with the reality of rapid construction of clean energy facilities.

This study aims to estimate the nonlinear distance decay of clean energy facilities in housing rental and sale markets. The contributions are as follows:

Firstly, we have focused on hydrogen refueling stations (HRS) in China and collected data with high-precision geographic locations and conduction time. China has the second-largest hydrogen refueling station networks in the world and deployment accelerates to 2700 in 2030 and 27000 in 2060 (IEA, 2021)[33], which means it is increasingly important to estimate the impact of hydrogen refueling stations. However, very few studies have focused on hydrogen refueling stations (O'Garra et al.,2008;[34] Yang et al.,2017[35]), compared to wind turbines and solar installations. We observed over longer geographic distances than current studies and also, we are the first to apply hedonic theory to assess the impact of hydrogen refueling stations.

Secondly, we relax the assumption of the form of distance decay. Existing research assumes the form of distance decay (Czajkowski et al.,2017)[36], and unless very explicit assumptions are used, the form of the equation is uncertain, therefore many scholars suggest introducing a nonlinear form (Hanley et al., 2003;[37] McMillen and Redfearn, 2010;[38] Letrémy and Katossky, 2014[39]). We use generated addictive model (GAM) to calculate and treat distance as a continuous variable. GAM has been widely used since 1987 (Hastie and Tibshirani,1987)[40]. Its advantages are that it does not preset the function form, and it is able to observe the changes affected by distance decay (Zemo et al., 2019; Łaszkiewicz et al., 2022). In addition, we also observed the average effect of distance on price through OLS, fixed effects and other methods, and verified the accuracy of the GAM results through distance group regression.

Thirdly, we will also examine the differences in the effects of different regions, and studies have shown that the distance attenuation effect is related to the attitudes or preferences of residents (O'Garra et al.,2008; Schumacher and Schultmann,2017[41]). However, residents' attitudes or preferences will show great differences due to their own interest framework and socio-economic factors (Lee et al., 2017)[42]. Since the socio-economic factors vary widely in different regions of China, it is necessary to compare the estimation results from different regions.

Fourthly, we have paid attention to the different impacts in the rental market and the sale market. Based on principal-agent theory, renters and homebuyers will show heterogeneous preferences (Wang and Lee, 2022)[43]. Existing research only focuses on the house sale market or the rental market and a few analyze both markets (Fuerst and McAllister, 2011;[44] Wang and Lee, 2022). Research conducted on sales and leases is often confronted with estimation bias due to heterogeneous issues, which means people tend to buy and hold high-quality assets, and rent low-quality assets (Hill and Syed, 2016)[45]. We use housing rental and sale prices from the same residence, which reduces possible estimation bias.

Our empirical analysis finds that distance decay is non-linear, and the impact of hydrogen refueling stations will change significantly with distances. Model comparison finds that spatial smooth coordinated by latitude and longitude of the transaction house can capture omitted spatial factors. Specifically, within 10km, for every 1% distance decreases, house prices will decrease by 6.67%. At the national level, the main impact distance of HRS is 3.5 km. Further, split incentives have been found on the impact of HRS, meaning that there is a significant impact on prices while no significant impact on rents in China. Besides, the impact of hydrogen refueling stations varies in different regions.

In this paper we proceed within the following structure: Section 2 is dedicated to the literature review on distance decay, model function, and split incentives. In Section 3 we discuss our methodology. Study area and data are introduced in Section 4. The results of the empirical study and region discussions are presented in Section 5 and 6. And finally Section 7 gives the conclusions and policy implications.

2. Literature review

2.1. Distance decay

The impact of energy infrastructure or environmental goods always decreases with spatial proximity decline, which is called "distance decay" (Swait et al.,2020)[46]. Distance decay may be due to the decrease in physical impact (Garcia-Gonzales et al., 2019)[47], amenity (Hanley et al., 2003; Łaszkiewicz et al 2022), and risk of disaster (Rajapaksa et al., 2017). The acceptance of residents has also been found related to distance decay. Mueller et al. (2017)[48] find spatial proximity had effects on residents' perceptions, attitudes and behavior. Swait et al. (2020) use data from a choice experiment about a park found that willingness to pay inferences concerning spatially distributed activities depends crucially on the spatial distribution of motivations for participation.

The attitudes of residents to energy facilities are very different. O'Garra et al. (2008) find a third of respondents in London are concerned by local hydrogen storage, and two-thirds believe its safety. Based on a questionnaire survey of 271 residents near the first HRS in the Netherlands, it is found that the public would have various emotions such as anger, fear, joy, and pride due to different perceptions (Huijts, 2018)[49]. Hoen et al. (2019)[50] find the ratio of positive to negative attitude towards wind turbines in US is approximately 7:1.

Besides, socio-economic characteristics significantly influence the attitudes and WTP (Willingness to Pay) (Lee et al., 2017)[51]. Population density and education levels have a negative association with the probability of biofuel plant location (Fortenbery et al.,2013)[52]. The support for nuclear power plant varies across population groups, for example, the low-income residents tend to support the nuclear power after recognizing its benefits (Uji et al., 2021)[53]. So, it is important to discuss the heterogeneity of spatial distribution.

The distribution of distance decay is not sure due to the above reasons. There is evidence that the function of willingness to pay distance decay can even make a vertical jump up or down due to a barrier like a toll bridge (Olsen et al., 2020)[54].

2.2. Model function form

Rosen (1974), Freeman (1979)[55], and others have stressed that economic theory does not suggest an appropriate functional form for hedonic price functions (Cassel and Mendelsohn, 1985)[56]. Spatial regression models are widely used to capture the distance decay effects and reducing spatial bias. Seo et al. (2019)[57] use a spatial error regression model to test the distance decay from the links and nodes of rail and highway infrastructure. Czajkowski et al. (2017) use a spatial lag model to value the willingness to pay for the nearest forest. But spatial regression models rely on spatial weighted matrixes, which requires prior knowledge.

McMillen and Redfearn (2010) affirm the use of the semiparametric model by comparing it with the parametric model. Letrémy and Katossky (2014) find that the fixed-parameter assumption is rejected, which confirms the need for flexible forms and the use of semiparametric models. While Olsen et al., (2020) find the differences between the different distance decay specifications are minor and the nonparametric approach performs as well as the parametric specifications.

One of the benefits of GAM is that it is data-driven and does not require any assumption on the function. But most of the studies using GAM in energy and environment areas only focus on the spatial fixed effects. For instance, Jensen et al (2018)[58] apply a spatial semi-parametric GAM with a smoothing spatial fixed effect to value the impact of on-shore wind turbine farms. Zemo et al (2019) also add a smoothing function using geographical coordinates of each property but assume a log in distance. And Jensen et al. (2021)[59] use a spatial-temporal control. Some studies use GAM to get more information about distance effects in advance. For example, Łaszkiewicz et al. (2019)[60] try to classify the green space as an environmental amenity or not with the help of GAM plots. Only Rajapaksa et al. (2017) and Łaszkiewicz et al. (2022) estimate the non-linear distance decay but they do not focus on the energy facilities.

2.3. Split incentives of renters and homebuyers

Split incentives have been found between renters and homeowners thanks to the principal-agent problem. Homeowners are sensitive to housing's proximity, while renters typically do not express 'Not In My Backyard' (Hankinson, 2018)[61]. Bernstein et al. (2019) find houses have a discount on sea level rise driven by sophisticated buyers worried about global warming, while no relation exists between sea level rise exposure and rental rates. In many cases, empirical analysis results illustrate that housing rents are affected but to a lesser level than the sale prices. Fuerst and McAllister (2011) find that the rental premia of office buildings with Energy Star or LEED eco-labels is less than the sale price premium in the US. The effects of flood-risk are qualitatively similar between rental and sale markets but the effect on rental prices is more muted than on sale prices (Pilla et al., 2019)[62]. However, some studies show different results of split incentives. Research on detached housing finds shared amenity spaces are likely to reduce the value of infill properties, while high-quality shared spaces might appeal to future rental markets (Iftekhar et al., 2022)[63]. Some studies find that renters and homebuyers have similar preferences (Wang and Lee, 2022).

The different study results mentioned above illustrate the different preferences of renters and homebuyers, and it is important to estimate the impact in housing rental and sale markets across different resident groups or regions. For instance, in high-rent cities, renters demonstrate NIMBY (Not In My Backyard) on par with homeowners because of price anxiety (Hankinson, 2018). And the impact of air quality on rental and sale prices in large and medium cities is higher than the small ones (Wang and Lee, 2022).

3. Methodology

Lancaster's (1966)[64] consumer theory states that the value of commodities, such as houses and lands, depend on their utility attributes or characteristics. Based on that, Rosen (1974) built the hedonic pricing model and defined hedonic prices as the implicit prices of attributes. Thus, marginal implicit prices can be identified by regressing housing prices on the characteristics that are valued by buyers and sellers.

The hedonic price function below maps the relationship between the price of house i, P_i, and its characteristics, including our focus variable of distance to hydrogen refueling station, z_i, and other characteristics, x_i, e.g., age, size and greening rate. From this function, we can obtain the estimates of the willingness to pay for marginal changes in distance to the nearest hydrogen refueling station.

$$P_i = f(x_i, z_i)$$

When estimating the WTP, there is a primary concern on the functional form. A linear impact or a predefined non-linear functional form is often used (Łaszkiewicz et al., 2022). However, the impact of distance to the nearest clean energy facility is expected to be non-linear with diverse visual views, various sensitivity and different acceptance levels of residents. Therefore, it is important to use a flexible functional form. Here we examined the functional form for our key variable, distance to the nearest HRS, by estimating different models. Specifically, the price function is estimated by linear models (LM) and a generalized additive model (GAM). In order to compare the difference between the rental and sale markets, we choose the natural logarithmic form of the house transaction price.

The first model is the simplest OLS model. Our independent variable is the natural logarithmic form of distance. OLS model estimation results are biased due to the omitted variable. Control variables are added to obtain a new linear model.

In these models, P_{it} is the transaction price of house i, at time t, $dist_i$ is distance to the nearest hydrogen refueling station, and $viirs_{it}$ is light brightness of the county where the house locates. Other characteristics of houses are also necessary for the model. $house_{kit}$ represents the attribute k of the residence itself, e.g., area, age, transaction amount and greening rate. $locat_{qit}$ represents the attribute q of the surrounding, e.g., number of subways within 1km, distance to central business center, and if it has a shop or office on the ground floor. β_s are estimated parameters and ε_{it} is the error term.

OLS model:

$$lnP_{it} = C + \beta_1 ldist_i + \varepsilon_{it} \tag{1}$$

LM:

$$lnP_{it} = C + \beta_1 ldist_i + \beta_2 viirs_{it} + \sum_k \beta_{3k} house_{kit} + \sum_q \beta_{4q} locat_{qit} + \varepsilon_{it} \tag{2}$$

The second concern about the model is the bias caused by unobserved factors. Fixed effects are added to reduce the bias. We add a spatial fixed effect, the county of the house, and time fixed effects, the transaction year and month, to LM and then get our fixed effect model. The time fixed effect can control the shock of external emergencies, e.g., a sudden change in real estate policy, and it can also control the difference in transactions between different months, as September, October and around the Spring Festival are the peak periods for real estate transactions in China. The spatial fixed effect can help control the influence of omitted spatial characteristics and it is important to choose the spatial scale. We test different spatial ranges in the pricing function (von Graevenitz and Panduro, 2015)[65], including the provincial level, city level and county level. Due to the great difference in the economic development level among the different counties even in the same city, it is reasonable to choose the county level fixed effect. Individual fixed effect is also added to get rid of variation between different HRS.

Fixed-effects model:

$$\begin{aligned} lnP_{it} = {} & C + \beta_1 ldist_i + \beta_2 viirs_{it} + \sum_k \beta_{3k} house_{kit} + \sum_q \beta_{4q} locat_{qit} + \sum tran\_time_t \\ & + \sum county_i + \sum hrs_i + \varepsilon_{it} \end{aligned} \tag{3}$$

Besides the fixed effects, as previous distance decay studies do (Zemo et al., 2019; Rajapaksa et al.,2017), we add a tensor based smooth, $f_3(long_i, latt_i)$, in the semi-parametric model, which is a smoothing function of the spatial coordinates capturing the exact location of the house (Rajapaksa et al., 2017). Although the spatial smooth may not fully address the problem of spatial autocorrelation (Dormann et al., 2007)[66], this approach avoids making assumptions about the structure and extent of the unobservable spatial process in data that often make the special error model and spatial lag model facing criticism. The spatial smooth can also account for the spatial heterogeneity not captured by the traditional spatial fixed effects and spatial autoregressive specifications (Montero et al.,2018)[67]. Comparing the results of model (3) and (4), we want to verify if spatial smooth can reduce bias due to unobserved spatial variables.

Spatial smooth model:

$$lnP_{it} = C + \beta_1 ldist_i + \beta_2 viirs_{it} + \sum_k \beta_{3k} house_{kit} + \sum_q \beta_{4q} locat_{qit} + \sum tran\_time_t + \sum county_i + \sum hrs_i + g(long_i, latt_i) + \varepsilon_{it} \quad (4)$$

The semi-parametric model is a general additive model (GAM), which is dependent on unknown smooth functions of predictors and estimated by quadratically penalized likelihood maximization (Wood, 2017)[68]. f_1 and f_2 are smooth functions. They are composed of different numbers of basis dimensions that can be changed by researchers. The distance to the nearest HRS has been described as nonparametric. The advantage is that we do not need a priori knowledge about the functional form of the relationship between explanatory and outcome variables (Łaszkiewicz et al., 2022). In order to avoid over-fitting estimates of f_1 and f_2, the model is fit by penalized likelihood maximization. In this model, the model likelihood is modified by the addition of a penalty for every smooth function's wiggliness. The number of spline basis functions is chosen to balance the wiggliness and badness of fit. This model can show us not only the impact distance of hydrogen refueling stations, but also the impact changing with the distance. It allows us to go beyond the simple conclusions about positive/negative/no association between the distance and house transaction prices (Bao and Wan, 2004;[69] Łaszkiewicz et al., 2022). Besides the distance, the light brightness of the county, $viirs$, is also set as a smooth function in order to reduce the fit bias, because the relationship between income and house transaction price is not always linear. As stated, we decide to use the semiparametric model with spatial smooth gradient since it is a priority for our research to explore the nonlinear relationship between the distance to the nearest hydrogen refueling station and the house transaction prices (Łaszkiewicz et al., 2019).

Semi-parametric model:

$$lnP_{it} = C + f_1(dist_i) + f_2(viirs_{it}) + g(long_i, latt_i) + \sum_k \beta_{3k} house_{kit} + \sum_q \beta_{4q} locat_{qit} + \sum tran\_time_t + \sum county_i + \sum hrs_i + \varepsilon_{it} \quad (5)$$

The attributes of houses and surroundings are still estimated as linear in the GAM and it becomes a semiparametric model. The semi-parametric model can be an attractive alternative to full nonparametric estimation suffering from a "curse of dimensionality", which means that the variance of the estimates increases rapidly by increasing the number of variables (McMillen, 2012)[70]. And it is starting to be recognized in the hedonic model (Jensen et al.,2021; Grislain-Letremy and Katossky, 2014;[71]).

The models are programmed in R and 'mgcv' package is used for the semi-parametric model to optimize the smoothness reliably. As REML is less prone to local minima than the other criteria and may actually be the most effective choice (Wood,2017), it is chosen as our smoothness selection criteria. For the fitness, we plot 4 standard diagnostic plots, some smoothing parameter estimation convergence information and the results of tests which may indicate if the smoothing basis dimension for a term is too low.

4. Study area and data

4.1. Study area

By the end of 2018, 26 hydrogen refueling stations had been established in China, excluding temporary hydrogen refueling stations established for large-scale events. Hydrogen refueling stations are distributed in eight provinces and are mainly located in urban areas. The competent authority for the construction of hydrogen refueling stations in China is not yet clear, and there is a lack of unified planning by the central government. Currently, the construction of hydrogen refueling stations is mainly driven by local governments. Different provinces have different regulations. In most provinces, the approval of construction land is under the responsibility of the natural resources department. In 2021, the provincial and municipal governments introduced the management measures for the construction and operation of hydrogen refueling stations, stipulating that hydrogen refueling station projects will be implemented following the oil or gas refueling station construction projects policy.

Our research sample includes seven different provinces in China, which are located in the eastern, northeastern, and central and western regions. From the geographical distribution perspective, the completed hydrogen refueling stations are concentrated in coastal areas, such as Guangdong, Shanghai, and Jiangsu. Some are distributed in the central and western provinces with abundant wind energy, solar energy, and hydropower, such as Henan, Hubei, Sichuan, and some are located in the northeastern provinces, for example, Liaoning has a hydrogen refueling station.

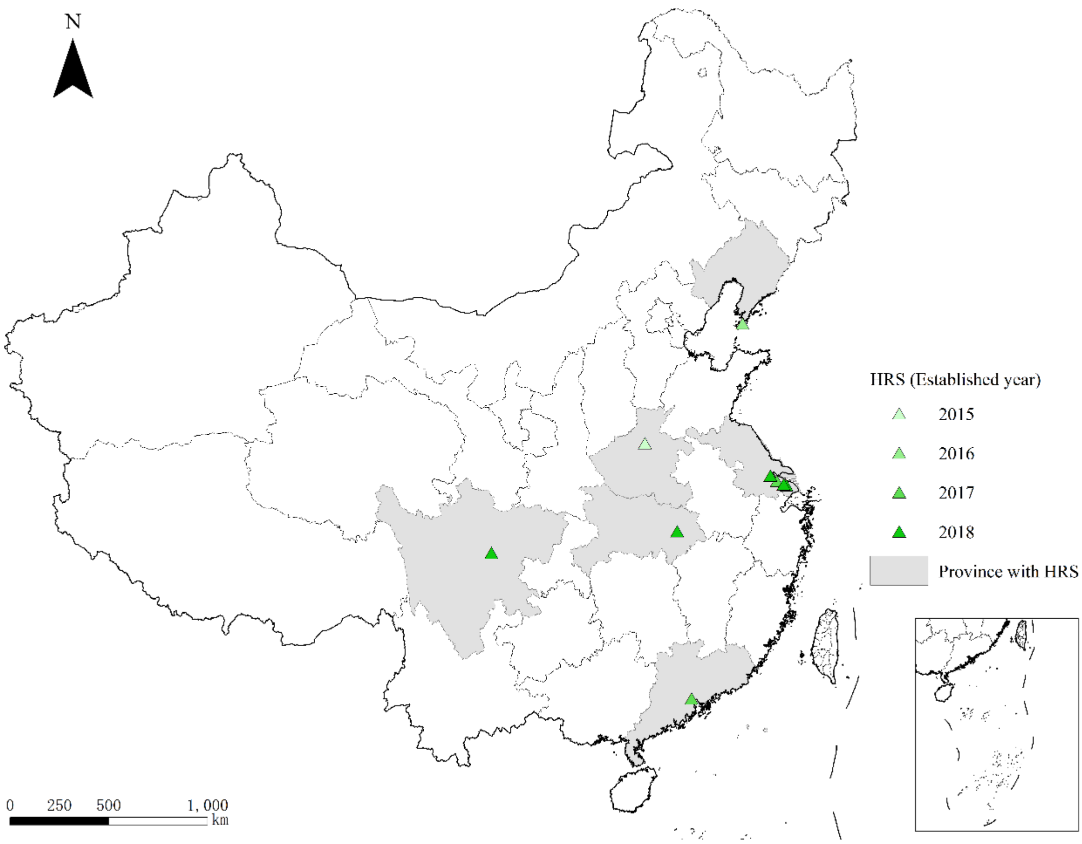

Fig.1. The distribution of established hydrogen refueling stations in China

4.2. Data

4.2.1. Distance to the nearest HRS

Distance to the nearest HRS is our focus independent variable in the semi-parametric model. In order to perform the data analysis, we use ArcGIS to match the houses in major cities with the HRS data according to geographic coordinates. And then the houses within 10km of the HRS will be collected for distance calculation. The reason is that first, according to the results of previous studies (Jarvis, 2021; Dröes and Koster, 2016), clean energy facilities will not affect the surrounding housing prices too far from them, so we do not need too much data; second, the addition of transaction prices data of houses that are too far away may cause interference and affect the accuracy of the results. The mean distance from the houses to the nearest HRS is 6.25km in China, the shortest distance is 250 meters. The mean distances in different regions are similar, 6.32km in eastern region, 6.64km in central and western regions, and 6.17km in northeastern region (Table A1).

In Fig.2 we can see the number of housing transaction at different distances. The closer the house is to the HRS, the more difficult it is to obtain the rental and sale data. But we still have 11% of the house transaction data within 3km of the HRS, which can ensure that a sufficient number of transactions are exposed to the HRS. In addition, the distance between the different HRS is far enough, so the same residence will not be affected by more than one HRS at the same time, preventing the superposition of the impact of HRS.

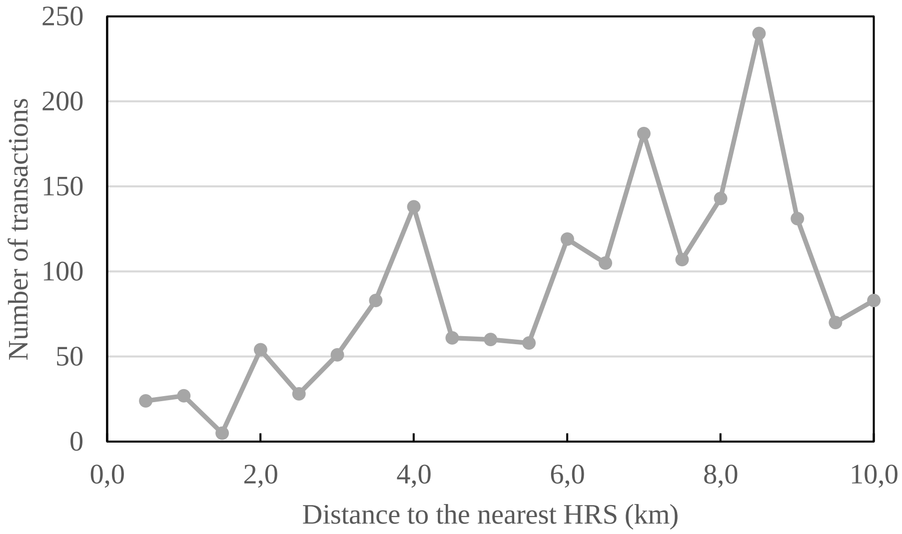

Fig.2 Number of housing transactions at different distances

4.2.2. House transaction prices

The housing rental and sale prices are the dependent variables of our study. The housing transaction prices are the monthly average transaction prices of the residence with longitude and latitude coordinates. Precise geographic coordinates enable the distance calculations. Compared with rental prices and the sale prices from different sources, rental prices and sale prices from the same residence can reduce the bias caused by unequal quality between the sold and rented dwellings (Hill and Syed, 2016). The database is from Shell Research Institute, which owns the massive real transaction data of the shell trading platform. The transaction prices from different years are 2012 prices adjusted for inflation.

The dataset used for our analysis contains 1768 rents and prices of houses traded in the period 2015-2018 in urban China. The rental price is from 8 RMB/m^2/month (USD

1.27) to 169 RMB/m^2/month as the cities where HRS location vary according to economic development. The mean sale price is 18135.75 RMB/m^2, and the gap between the minimum and maximum prices is pretty high because of the different types of the houses, which means it is necessary to control the *villa* variable.

The mean housing rental and sale prices are the highest in east region, while in central and west regions they are the lowest. Considering the minimum and maximum transaction prices in different regions, we find that the difference in minimum prices is not obvious, while the difference in maximum prices is huge.

4.2.3. Control variables

The characteristics of houses are from the same database as house transaction prices, including size, age, greening rate of the residence, and whether it has a shop or office on the ground floor. The number of subways within 1km of the residence is calculated by ArcGIS using Subway stations and lines dataset in mainland China from Urban Data Party[72]. The dataset was constructed base on the subway map of each city and combined with public information of planning and construction of each line and station until 2020. The distances to CBD are calculated in the same way with our focus variable. Night light brightness data is from National Oceanic and Atmospheric Administration, and can be regarded as a measure of economic activity. Compared with other data, it can reflect population density and economic development more objectively (Gibson et al., 2021)[73].

Table 1 Descriptive statistics of variables

Variables	Descriptions	Obs.	Mean	Std. Dev.	Min	Max
rentprice	Rental prices of the house in China (RMB/m^2 /month)	1768	34.39	16.64	8	169
saleprice	Sale prices of the house in China (RMB/m^2)	1768	18135.75	11610.29	6142.26	91617.37
dist	Distance from the house to the nearest hydrogen refueling station	1768	6.25	2.35	0.25	9.92
size	The size of the house (m^2)	1768	77.71	25.65	23	244
villa	Whether it is a villa	1768	0.05	0.22	0	1
office	Whether it has a shop or office on the ground floor	1768	0.20	0.40	0	1
green	The greening rate of the residence	1768	35.98	7.17	20	60
age	The age of the house	1768	3.18	1.18	0	8
numsub	Number of subways around the house within 1km	1768	0.61	0.82	0	3
lCBD	Ln distance to the central business district	1768	9.24	0.86	6.69	10.70
viirs	Night light brightness	1768	18.39	10.95	3.72	56.11

5. Results

5.1. Model comparison

Before getting the final estimated results, we test multicollinearity of the variables by the variance inflation factor (VIF). In Table 2 we observe that the VIFs are consistently below 5 which is the suggested value (Rogerson, 2001), thus all the variables have passed the test.

Table 2 VIF of all the variables

	ldist	size	villa	office	green	age	numsub	lCBD	viirs
VIF	1.287	1.174	1.144	1.057	1.076	1.152	1.138	1.874	1.682

The regression results for the four models are shown in Table 3 and Table 4. We first estimate the simplest OLS, and then observe the changes in the estimated parameter of our focus variable, *ldist*, when adding control variables. Although sometimes the results with some of the control variables are not significant, they are still put in the models to keep the same (same what? Same parameters? Same …?) for house rental price and sale price models, which will make possible the comparison of results across different markets. Based on the model with control variables, a series of fixed effects are added, including time fixed effects, spatial fixed effect and HRS's individual fixed effect, to control the impact of time and location of house transaction. And we find that adjusted R-square increases from 46.98% to 69.68% in rental market and from 50.87% to 80.94% in sale market, which indicates the significant increase of the interpretation level of our model. The addition of spatial smooth makes the coefficients of *ldist* insignificant, suggesting that spatial smooth may capture more spatial features than the fixed-effects model. Most importantly, we change the function of distance and light brightness variables to nonlinear and use the spatial smooth coordinated by latitude and longitude of the transaction house. As shown in the Table 3 and 4, the semiparametric model has the highest adjusted R-square. AIC (Akaike Information Criterion) estimates the quality of our models and the results show the semi-parametric model has the least information loss.

We plot the residuals of focus variable, *ldist*, in LM and fixed effects model (Fig.B1 and Fig.B2). It shows that the fixed effects model has better fitness than the model only with control variables, whose residual is seemed to be distributed on both sides of the estimated line evenly. However, many parts have not been explained yet.

Furthermore, the result of the semi-parametric model provides another evidence that it is necessary to use a nonlinear distance form. A big EDF (Effective Degrees of Freedom) indicates a highly nonlinear relationship (Zuur et al., 2009)[74]. When the EDF is equal to 1, it indicates the linear relationship between dependent variable and the core independent variable. It is obvious that in our results shown in Table 5, EDF is greater than 2, which rejects the linear relationship and shows the existence of highly non-linear distance decay. According to the p-value, all the three non-linear terms are significant and that means the probability of the coefficient of all basis functions of the given covariate being zero is close to 0.

Table 3 Estimated results from four models with rental price

	OLS	Control	Fixed effects	Spatial smooth	Semi-parametric
Intercept	3.3210***	2.0943***	3.8924***	0.0000	2.7433***
	(0.0306)	(0.1366)	(0.2207)	(0.0000)	(0.7646)
ldist	0.0710***	0.1465***	0.0577***	-0.0106	
	(0.0169)	(0.0140)	(0.0124)	(0.0146)	
size		0.0033***	0.0024***	0.0019***	0.0018***
		(0.0003)	(0.0003)	(0.0003)	(0.0002)
villa		-0.0632.	-0.0393	0.0616.	0.0486
		(0.0357)	(0.0312)	(0.0345)	(0.0344)
office		0.2252***	0.1725***	0.2001***	0.1807***
		(0.0191)	(0.0162)	(0.0156)	(0.0157)
green		0.0026*	-0.0006	-0.0015.	-0.0007
		(0.0011)	(0.0009)	(0.0009)	(0.0009)
age		0.0465***	0.0088	-0.0020	-0.0024
		(0.0067)	(0.0069)	(0.0063)	(0.0064)

numsub		0.0346***	0.0519***	0.0476***	0.0411***
		(0.0096)	(0.0087)	(0.0080)	(0.0079)
lCBD		0.0153	-0.1296***	-0.0994***	-0.0905***
		(0.0119)	(0.0162)	(0.0211)	(0.0224)
viirs		0.0213***	0.0096***	0.0060***	
		(0.0009)	(0.0010)	(0.0012)	
Year	N	N	Y	Y	Y
Month	N	N	Y	Y	Y
County	N	N	Y	Y	Y
HRS	N	N	Y	Y	Y
Spatial smooth	N	N	N	Y	Y
R-sq.(adj)	0.0094	0.4698	0.6968	0.759	0.771
AIC	2000.36	903.18	-59.20	-453.93	-528.28
n			1768		

Standard errors in parentheses. Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 4 Estimated results from four models with sale price

	OLS	Control	Fixed effects	Spatial smooth	Semi-parametric
Intercept	9.5475***	5.7524***	9.1874***	0.0000	5.487***
	(0.0330)	(0.1418)	(0.1888)	(0.0000)	(0.6270)
ldist	0.0769***	0.1817***	0.1026***	0.0662***	
	(0.0182)	(0.0145)	(0.0106)	(0.0122)	
size		0.0047***	0.0020***	0.0009***	0.0010***
		(0.0003)	(0.0002)	(0.0002)	(0.0002)
villa		0.0835*	0.0416	0.2332***	0.2263***
		(0.0371)	(0.0267)	(0.0277)	(0.0275)
office		0.1121***	0.0051	0.0152	-0.0072
		(0.0198)	(0.0139)	(0.0120)	(0.0126)
green		0.0060***	0.0049***	0.0044***	0.0051***
		(0.0011)	(0.0008)	(0.0007)	(0.0007)
age		0.0458***	-0.0021	-0.0099*	-0.0117*
		(0.0070)	(0.0059)	(0.0049)	(0.0050)
numsub		0.0401***	0.0308***	0.0298***	0.0316***
		(0.0100)	(0.0074)	(0.0061)	(0.0062)
lCBD		0.2551***	-0.0184**	0.0219	0.0627***
		(0.0124)	(0.0138)	(0.0164)	(0.0181)
viirs		0.0263***	0.0082***	0.0006	
		(0.0009)	(0.0009)	(0.0009)	
Year	N	N	Y	Y	Y
Month	N	N	Y	Y	Y
County	N	N	Y	Y	Y
HRS	N	N	Y	Y	Y

Spatial smooth	N	N	N	Y	Y
R-sq.(adj)	0.0094	0.5087	0.8094	0.8780	0.8850
AIC	2269.20	1037.336	-611.33	-1381.01	-1467.53
n			1768		

Standard errors in parentheses. Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 5 Approximate significance of smooth terms

	k	EDF	p-value
RENT			
dist	9	6.81	< 2e-16***
viirs	9	7.03	< 2e-16***
long, latt	24	13.83	< 2e-16***
SALE			
dist	14	11.91	< 2e-16***
viirs	9	6.36	< 2e-16***
long, latt	24	15.68	< 2e-16***

Signif. codes : 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

5.2. Distance decay effects

By focusing on the estimated parameters of distance, we find no evidence to reject the existence of the distance decay effect of HRS in sale market while in rental market, results will be different.

In rental market, the coefficients of *ldist* from model (1)-(3) are positive and significant, indicating the impact level of HRS is decreasing when the distance is increasing. But in spatial smooth model, the coefficient is no longer significant, implying that distance decay does not exist in the rental market. Differences in results suggest that the distance decay shown in models (1)-(3) may be caused by spatial omitted variables.

In sale market, results from model (1)-(4) prove that there is a decrease in the impact of HRS on housing prices as the distance increases. Within the range of 10km, for every 1% decrease in the distance from the houses to the HRS, the sale prices decrease by 6.62%. However, the explanation is limited in two aspects. One is that it is impossible to know the main geographical range of the impact of the HRS, which is very important for policy makers. The other one is what we obtain from the coefficient is an average estimated value, ignoring the different impact of HRS at different distances.

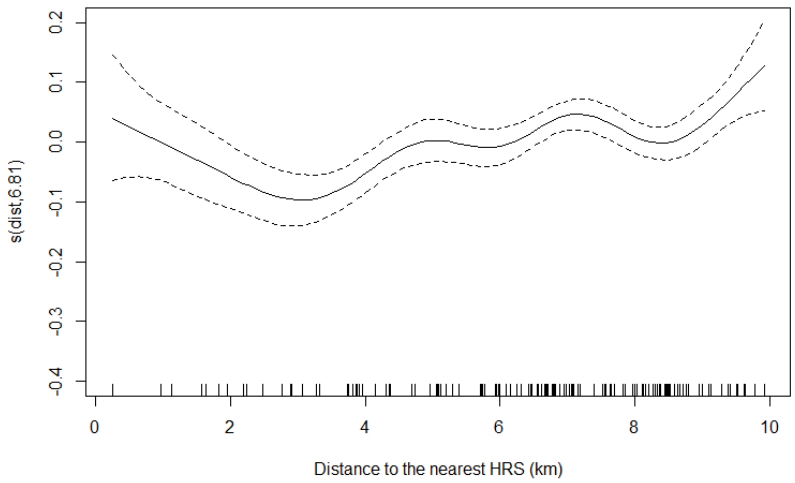

Fig. 3 Estimated curve in house rental market across China

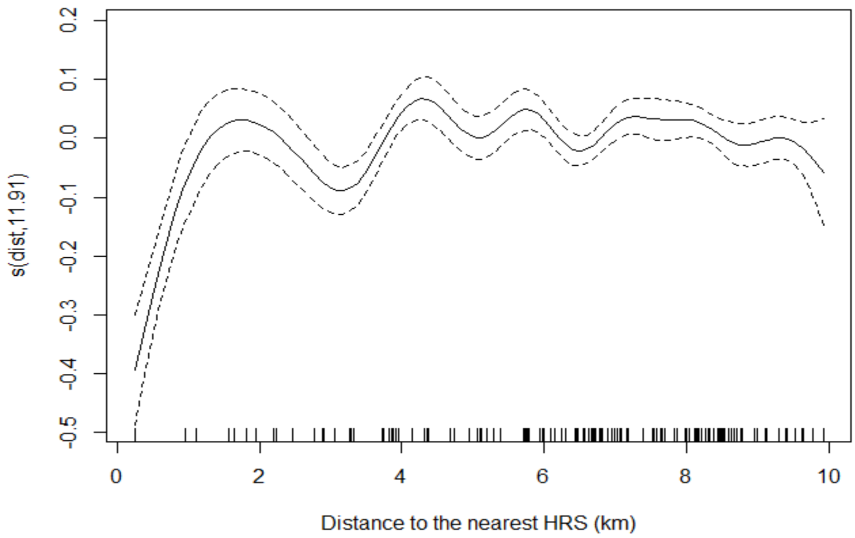

Fig.4 Estimated curve in house sale market across China

Fig. 3 and Fig. 4 from the results of our semi-parametric model illustrate that the impact of HRS varies at different distances, and the characteristics of distance decay curves vary in different markets. In the house rental market, there is a slight positive effect within 500 meters, and a possible negative effect between 500 meters and 4 kilometers. But after 4 km the rent can be considered with less impact as the estimated curve fluctuates around the zero-impact line. In the sale market, the main impact distance is 3.5 km, and the impact stops decreasing. There is huge difference in the impact between the rent and sale market, which is shown as the large difference in the volatility of the two estimated curves in the two markets.

Fig.3 shows that the estimated curve is basically stable in the rental market, while in the sale market (Fig.4), a substantial drop in house prices can be observed at the same distance. The closer to the HRS, the more the house price drops, and the drop even reaches beyond 10%. Actually, very few HRS were built within 500 meters of a residence before 2018 so we need more evidence to confirm the impact level.

One possible reason for the difference between the rental and sale market is that in some urban areas, the implementation of HRS means the development of new industries, which drives population agglomeration and increases housing rents within 2km. Another reason is that compared with the sale market, house rental market adjusts more flexibly, driving people who have a positive preference for HRS approach faster.

Results for control variables reveal heterogenous preferences for renters and homebuyers. Renters are concerned about the size of the house (whether it has a shop or office on the ground floor), number of subway and distance to CBD. Buyers also pay attention to the type of house (whether it is a villa), the greening rate, the age of the house. The estimated curves of night light brightness show that with the increase of brightness, the house transaction price will increase at first, but fluctuate after the brightness reaches a certain level.

5.3. Robustness check

As Wood (2017) recommends, when the EDF approach k, checking can be important. The robustness of the semi-parametric model will be checked in two ways. First, we are going to increase the value of k. We will change the number of basis dimension to see the difference between the new curves and the old ones, and check if there is a pattern in the residuals that could potentially be explained by increasing k. Specially, ks are increased to 15 and 20, and the main results do not change after more details are added to the curves (Fig. B3).

The result table from 'gam.check' shows the EDF is greater than k-1, which means that our results are robust. For the rental market (Fig.5), the Q-Q plot shows the model fits well though the left ends have some extreme outliers that causes some loss of accuracy. The figure about residuals against the linear predictor shows a roughly horizontal band around the zero-residual line. In the histogram of residuals figure, the higher rental prices have a little dispersion, but most of the residuals evenly distribute on both sides of 0. We can also observe only a few of outliers in the response against fitted values plot. The model fitness for the sale market is much better (Fig.6). The deviance residuals are close to the theoretical distribution. The residuals evenly distribute on both sides of 0. The residuals are well distributed around zero against the linear predictor. We can observe that all points are on or very close to a 45-degree-angle line, which indicates that the two values match up well.

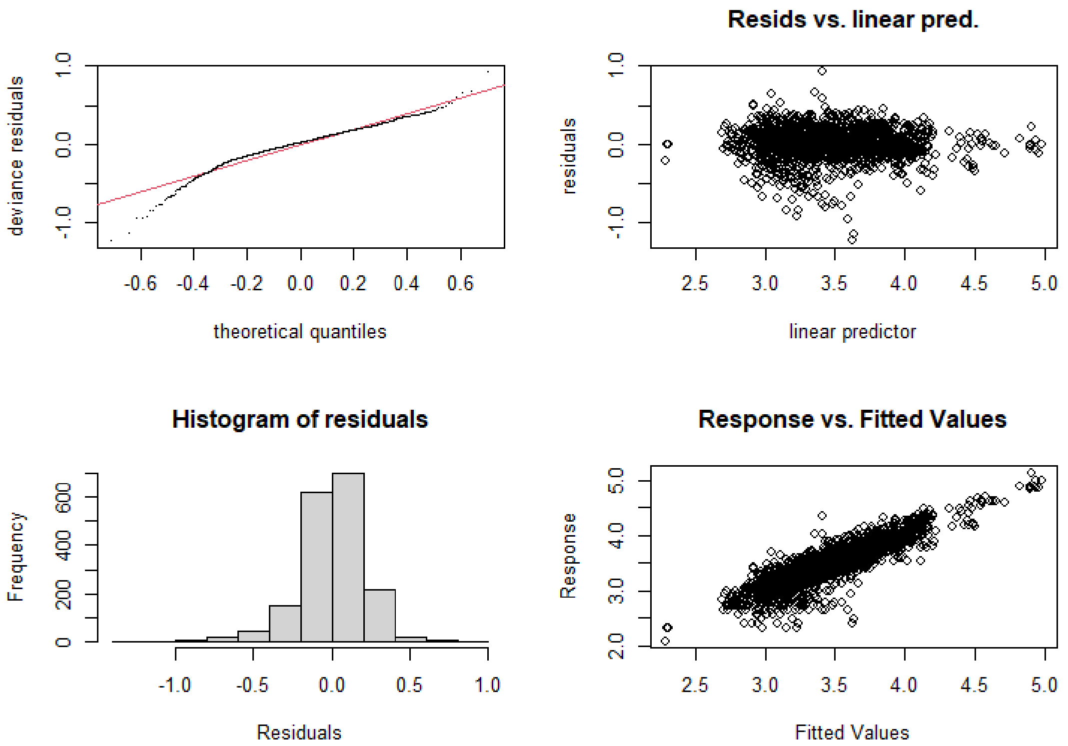

Fig.5 Model fitness for the rental market

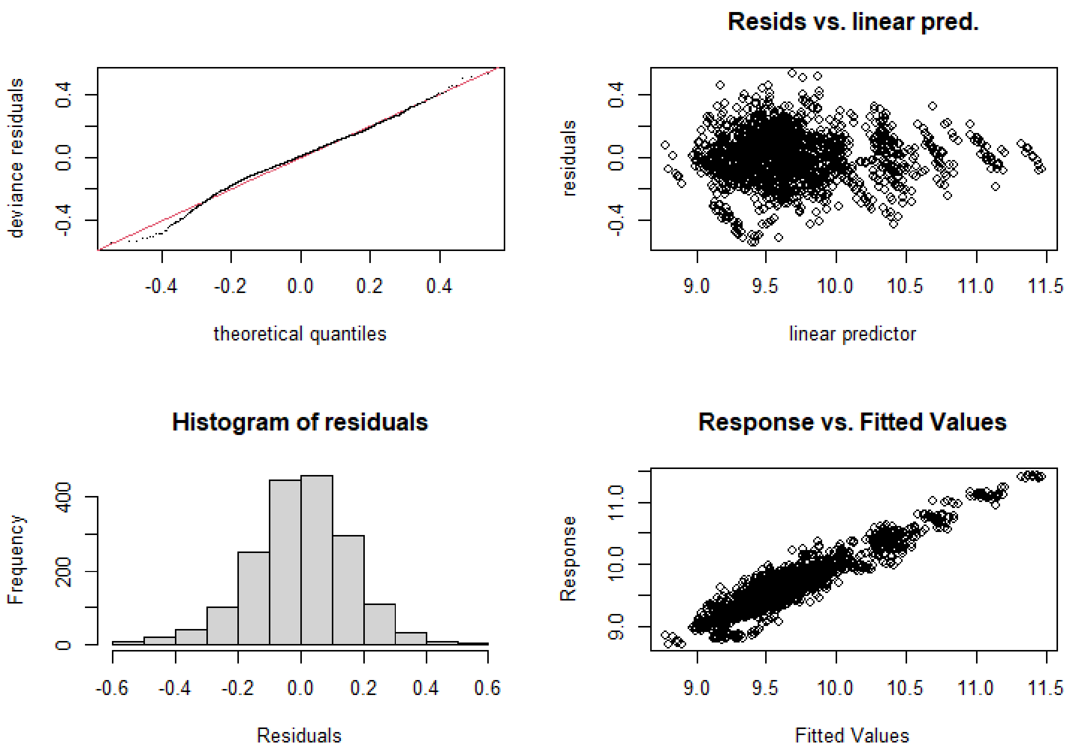

Fig.6 Model fitness for the sale market

Second, we use another econometrics model in which the distance is divided into 20 groups, and group distance is 500 meters. When the distance of each group is small enough, we can get a curve that varies with distance after evaluating the average effect of each group. In this econometrics model, the same fixed effects and spatial smooth of model (4) are added in order to reduce omitted bias. It is found that the shapes of the new curves are similar to our main result curves (Fig.7). The estimated curve fluctuates around the 0 level in the rental market. The impact distance is nearly 4 km in the sale market. Specifically, there is a positive impact within 500 meters in the rental market but a deep sharp negative impact within 4 km in sale market. Table A2 in appendix shows that most of the distance group variables are insignificant in the rental market. The coefficient of dist03 (1.5 km) in sale market is positive but insignificant. The positive coefficient of dist04 (2 km) may be caused by unobserved variables.

However, the distance group model will face the problem of gap choosing. We have to balance the number of groups and the distance of each group. And the coefficients only show the average impact of certain distance groups.

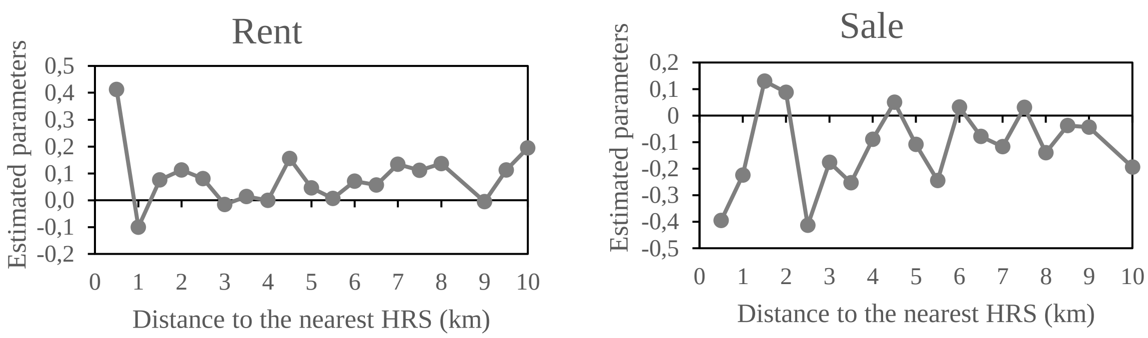

Fig.7 Results from distance group estimation

6. Discussion

To test the spatial heterogeneity, we evaluate the impact in eastern, central and western, and northeastern regions with our semi-parametric model. One reason to choose these regions is that they have been subjected to differentiated and targeted policies in the past decades. Since the Reform and Opening-up, Chinese government has encouraged the eastern region to take the lead in economic development, and then modernization. For other regions, there are different strategies and policies such as the Great Western Development Strategy, the Rise of Central China, and the Revitalization of the Northeast.

Another reason is the difference in resident's preference. The public income level, consumption level, education level and macroeconomic development level would all influence the public demand for the environment (Li Z et al., 2022)[75]. There are huge differences in the level of economic development in eastern, central, western and northeastern China. Eastern region has the highest level of economic development, and the per capita disposable income of residents was 39,438.9 RMB in 2019, while it was 26,025.3 RMB in the central region, and only 23,986.1 RMB in western region, and 27370.6 RMB in northeastern region. (NBSC,2020)[76]. Residents in these regions also have different education level. Central and western region has the highest proportion of primary education, while eastern region has the highest proportion of high school education (Liu et al., 2018)[77]. As mentioned above, residents' attitudes towards HRS can be captured by housing transaction prices and may lead to different results. So, it is necessary to observe the different regions in China.

We substituted the data of housing transaction prices and HRS belonging to different regions in the semi-parametric model, and tested the *k* value. The fitness is improved by increasing the number of basis dimensions until the results no longer changed significantly, even if this may expose us to some risk of overfitting. The model fitness tests are shown in Fig.B.4-10.

Table 6 Estimated results from semi-parametric model in different regions

	East		Central and west		Northeast	
	RENT	SALE	RENT	SALE	RENT	SALE
Intercept	2.5149	122.20*	0.0000	0.0000	5.3194***	0.0000
	(6.1818)	(50.28)	(0.0000	(0.0000)	(0.3278)	(0.0000)
size	-0.0032***	0.0003	-0.0021***	-0.0010.	0.0032***	-0.0005*
	(0.0003)	(0.0002)	(0.0006)	(0.0005)	(0.0003)	(0.0002)
villa	0.1075**	0.3092***	-0.2969.	1.3210***	-0.0981	-0.6891***
	(0.0378)	(0.0362)	(0.1526)	(0.1970)	(0.1236)	(0.1305)
office	0.1300***	-0.0808***	0.2422**	0.2537**	-0.0425	-0.0717***
	(0.0244)	(0.0189)	(0.0796)	(0.0847)	(0.0261)	(0.0180)
green	-0.0035	0.0074***	0.0094	-0.1401**	-0.0018	0.0060***
	(0.0028)	(0.0022)	(0.0344)	(0.0445)	(0.0012)	(0.0010)
age	-0.0091	-0.0034	-0.0679**	0.0073	-0.0099	0.0087
	(0.0116)	(0.0128)	(0.0229)	(0.0266)	(0.0083)	(0.0062)
numsub	0.0335.	-0.0048	-0.1812	0.7317***	-0.0317**	-0.0001
	(0.0172)	(0.0161)	(0.1225)	(0.1155)	(0.0116)	(0.0087)
lCBD	0.1394	-10.51*	-1.7630***	2.2060	-0.1986***	0.0784**
	(0.6131)	(4.9380)	(0.2921)	(1.9720)	(0.0336)	(0.0258)
Year dummy	Y	Y	Y	Y	Y	Y
Month dummy	Y	Y	Y	Y	Y	Y
County dummy	Y	Y	Y	Y	Y	Y
Spatial smooth	Y	Y	Y	Y	Y	Y
R-sq.(adj)	0.951	0.972	0.892	0.924	0.708	0.815
n	444		175		1149	

Standard errors in parentheses. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 7 Approximate significance of smooth terms in different regions

	East			Central and west			Northeast		
	k	EDF	p-value	k	EDF	p-value	k	EDF	p-value
RENT									
dist	14	9.76	<2e-16***	9	2.47	<2e-16***	14	12.93	<2e-16***
viirs	9	1.08	0.575	9	4.48	0.04 *	9	5.42	0.015*
long, latt	24	7.87	0.005**	24	3	0.005**	24	18.43	<2e-16***
SALE									
dist	9	6.63	<2e-16***	9	2.45	<2e-16***	14	13.35	<2e-16***
viirs	9	5.87	<2e-16***	9	3.28	0.045*	9	8.16	<2e-16***
long, latt	24	14.06	<2e-16***	24	3.44	0.37	24	22.88	<2e-16***

Signif. codes : 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

6.1. Eastern region

In the rental market in the eastern region, the HRS has a negative impact on the house rental prices, and as the distance increases, the impact gradually decreases, which reveals the existence of the distance decay. The curve is below the 0-horizontal line within 3km, and fluctuates around 0 after 3km, which means the impact distance of the HRS in eastern region is 3 km. In the sale market, HRS has a great negative impact on housing prices. Within 5 km, the decline in housing prices gradually narrows and decreases to 0 with the distance increasing. The volatility range of its 95% confidence interval also bears out this trend.

By comparing the results for the rents and prices of the houses around the HRS in the eastern region, we observe that both of them have a falling trend, but the price reduction in the sale market is even greater.

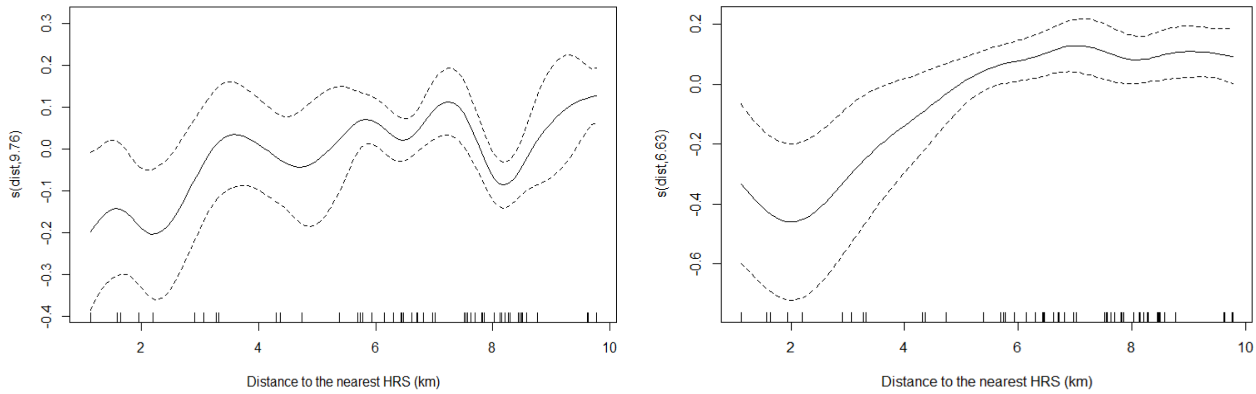

Fig.8 Estimated curves in eastern region

6.2. Central and western regions

There are fundamentally different results across the markets in the central and western regions. Fig.9 shows that there is a stable increase in the rent of houses within 7 km around the HRS. On the contrary, the sale price of the houses decreased significantly. We believe these completely opposite results are justified, as the construction of the HRS may represent the development of new industries in the area, leading to an increase in the area's population and an increase in housing rents, which explains why the increase in rents is more geographically widespread and the impact hardly changes within 5km. While in the sale market, homebuyers are more sensitive to the risks posed by HRS. Consistent with our main conclusions, housing prices around HRS declined. For consumers, the preferences for house rental and house purchase are different. Renting a house may be a short-term decision, and the cost of replacing rental houses is lower, while buying a house is a long-term decision, so it is more concerned about the long-term environment and health risk of HRS. Another possible reason is that the price changes in the rental market are more flexible. But the construction time of HRS in the central and western regions is relatively short, so it is necessary to observe the changes in housing prices in a longer time window.

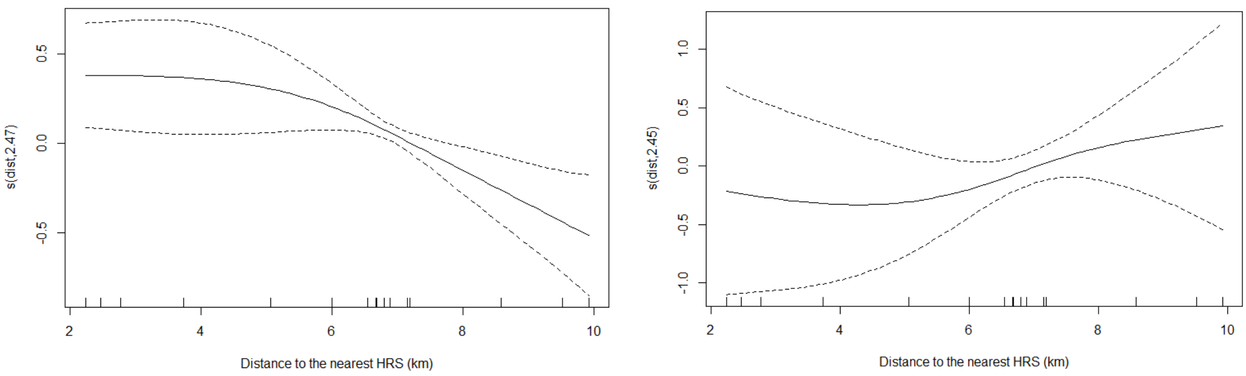

Fig.9 Estimated curves in central and western region

6.3. Northeastern region

In the northeastern region, the curve in the rental market fluctuates around the horizontal line, which means that the HRS has no significant impact on the rental price of the surrounding houses. In the sale market, HRS may have a negative impact on house sale prices within 1.5 km of the HRS but with a large confidence interval.

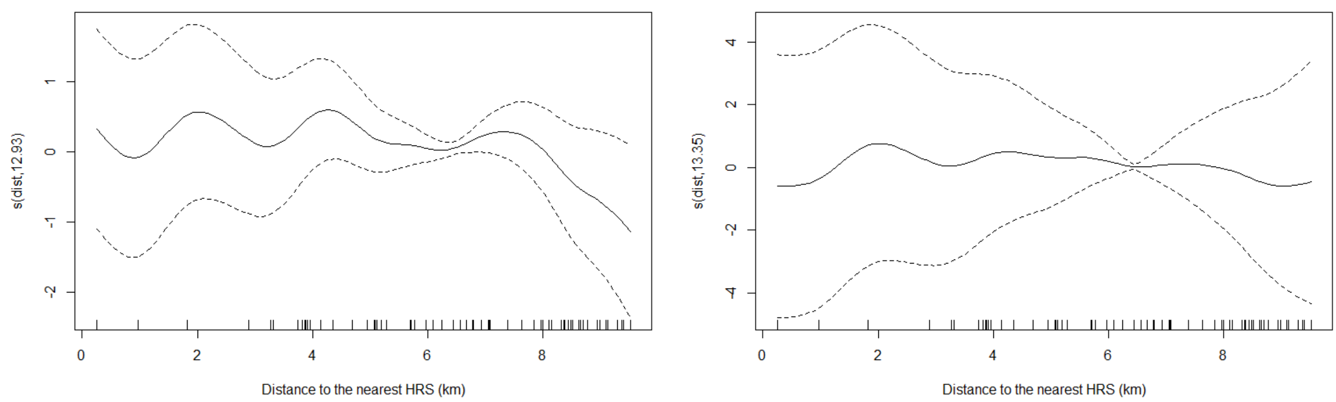

Fig.10 Estimated curves in northeastern region

7. Conclusions and Policy Implications

Hydrogen has become an integral part of China's future national energy system. Promoting the construction of hydrogen refueling stations (HRS) can give full play to the clean and low-carbon characteristics of hydrogen and promote the green transformation of the transportation industry. With the rapid growth of number of HRS, the negative impact of the facilities will become more and more obvious. Therefore, valuing the impact of existing HRS can be an important policy reference for future construction. Based on hedonic theory, in this study we estimated the non-linear distance decay effects of HRS using housing transaction data from 2015-2018. We proceeded first by valuing the impact of HRS under hedonic theory framework; then we relaxed the linearity assumption in the estimation and visualized the impact of HRS at different distances rather than only estimating the average impact, which helps to identify the main impact distance of HRS. Thereafter, we estimated the impact in different regions, and finally, we compared the different impacts of HRS between house rental and sale markets.

Several interesting findings have been identified in our study. First, we realized that the semi-parametric model used with spatial smoothing is more capable to reduce the bias caused by omitted variables and model specification. Second, the construction of HRS will lead to split incentives. At the national level, there is no significant impact on house rents, but it will lead to a significant reduction in house prices within 3.5 km. For every 1% distance decreases, house prices will decrease by 6.62%. Third, the impact of HRS varies in different regions due to different socio-economic factors and residents' preferences. In eastern region, the HRS has a negative impact on both rental and sale markets. In central and western regions, the impact on rental prices is positive but negative on sale prices. In northeastern region, the impact is not significant. The results corroborate the findings of previous research that people in high-rent areas may be more sensitive to the facility construction (Wang et al., 2022[78]; Hankinson, 2018), and people in low-income areas are more tolerant to the possible negative impact of facilities (Uji et al., 2021).

These conclusions provide some references for policy making. First of all, when constructing clean energy facilities, it is necessary to take into account their possible negative impact on surrounding residents. Specifically, facilities should be built as far away as possible from the residential areas so as to reduce the impact. Secondly, the policy for the construction of hydrogen refueling stations should be adapted to local conditions. Residents in different regions have different preferences. Before construction, public opinion should be fully listened and the public participation process should be strictly implemented. This is very much conducive for reducing the risk of local residents' opposition to the facility construction. Besides, we must focus not only on the financial loss that the homeowners may face, but also on the loss and anxiety of renters in high-rent areas.

Although this study provides several insights about the distance decay effects of HRS, further studies can be considered. For instance this study does not show the impact variation of HRS over time. Since the impact of HRS is related to residents' attitudes that may change with their perception of HRS, it is necessary to observe the changes in the impact at different times. In addition, due to the limitation of housing transaction data, the hydrogen refueling stations estimated in this study are all located in cities, and it is also necessary to value the impact of HRS far away from urban built-up areas. This shall be taken into account and overcome in the future research.

Appendix A

Table A.1 Descriptive statistics of variables in different regions

	East				Central and west				Northeast			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
rentprice	43.53	24.98	16	169	23.10	5.33	8	37	32.58	11.22	10	63
saleprice	30619.64	16788.35	7889.53	91617.37	13135.17	2840.38	6142.26	18169.31	14073.31	4109.99	6573.27	32122.67
dist	6.32	2.27	1.12	9.77	6.64	2.46	2.24	9.92	6.17	2.36	0.25	9.52
size	90.69	31.31	32	244	83.84	16.91	50	129	71.76	22.02	23	227
villa	0.17	0.38	0	1	0.05	0.22	0	1	0.01	0.07	0	1
office	0.27	0.45	0	1	0.20	0.40	0	1	0.17	0.38	0	1
green	34.71	4.50	20	45	29.73	1.85	25	35.3	37.42	7.88	20	60
age	3.80	0.95	2	8	3.23	1.51	0	6	2.93	1.10	0	7
numsub	0.45	0.66	0	3	0.16	0.41	0	2	0.74	0.89	0	3
lCBD	10.18	0.44	9.14	10.70	9.53	0.60	8.76	10.35	8.83	0.70	6.69	9.79
viirs	18.64	9.82	6.42	50.18	13.29	3.69	3.72	19.57	19.07	11.87	7.35	56.11
Obs	444				175				1149			

Table A.2 Results from distance group estimation

	RENT	SALE
Intercept	16.90	135.5***
	(12.02)	(30.68)
dist01	0.4122***	-0.3949***
	(0.0794)	(0.0617)
dist02	-0.0999.	-0.2245***
	(0.0602)	(0.0484)
dist03	0.0762	0.13
	(0.1063)	(0.0840)
dist04	0.1124*	0.0873*
	(0.0516)	(0.0413)
dist05	0.0800	-0.4135***
	(0.0656)	(0.0536)
dist06	-0.0164	-0.1759***
	(0.0583)	(0.0471)
dist07	0.0140	-0.2531***
	(0.0499)	(0.0418)
dist08	0.0499	-0.0896*
	(0.0442)	(0.0370)
dist09	0.1551**	0.0507
	(0.0497)	(0.0393)
dist10	0.0465	-0.1082**
	(0.0462)	(0.0390)
dist11	0.0067	-0.2449***
	(0.0455)	(0.0367)
dist12	0.0713.	0.0317
	(0.0431)	(0.0341)
dist13	0.0572	-0.0784*
	(0.0436)	(0.0343)
dist14	0.1335***	-0.1172***
	(0.0401)	(0.0317)
dist15	0.1116**	0.0304
	(0.0415)	(0.0316)
dist16	0.1359**	-0.1401***
	(0.0424)	(0.0347)
dist17	-0.0050	-0.0382
	(0.0327)	(0.0248)
dist18	0.1129**	-0.0442
	(0.0381)	(0.0283)
dist20	0.1948***	-0.1948***
	(0.0512)	(0.0412)
Control	Y	Y
Year	Y	Y
Month	Y	Y
County	Y	Y
HRS	Y	Y
Spatial smooth	Y	Y
R-sq.(adj)	0.774	0.894

n	1768

Standard errors in parentheses. Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Appendix B

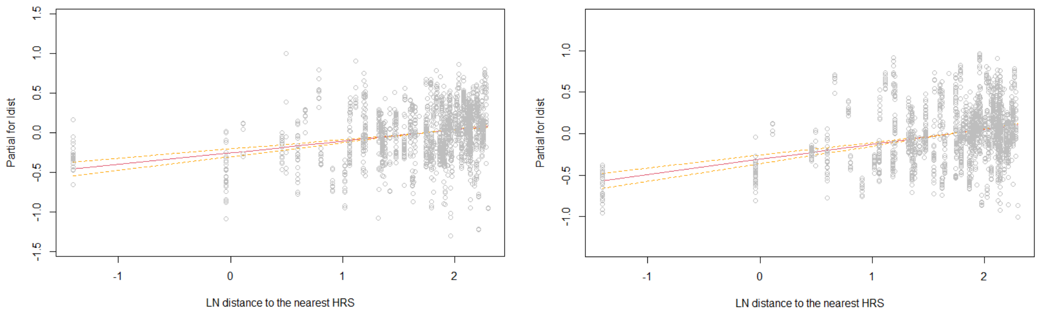

Fig.B.1 LM residuals
(Figure on the left is the rental market, right is the sale market. Same in figures below.)

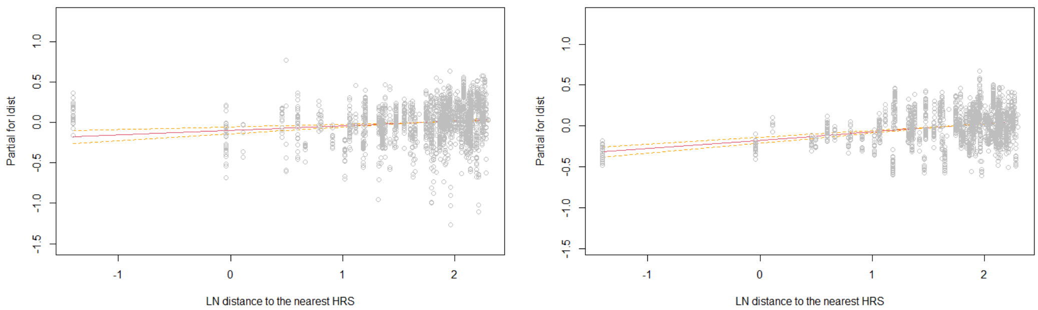

Fig.B.2 Fixed effects model residuals

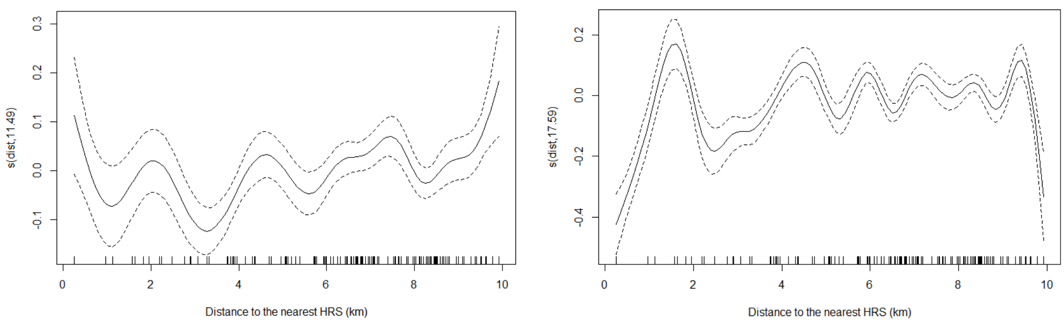

Fig.B.3 Robustness check of estimated curves in house rental (left, k=15) and sale market (right, k=20) across China

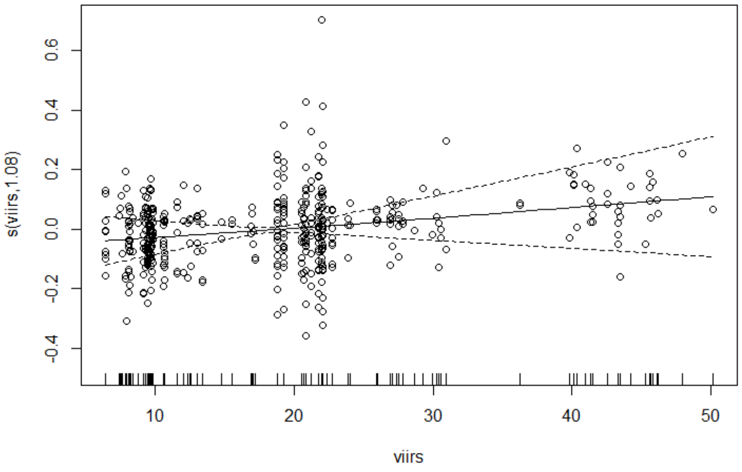

Fig.B.4 The relationship between night light brightness and house rental prices in eastern region

The value of k for *viirs* is close to 1 in the rental market (Table 7), but it does not mean that the relationship between the night light brightness and house rental prices is strictly linear. When the dataset is concentrated at some certain points, the model may make linear estimates by fault (Wood, 2004)[79]. So, we plot the estimated curve of night light brightness with residuals and find that the value of brightness is concentrated at 10-20 and the relationship is certainly not linear.

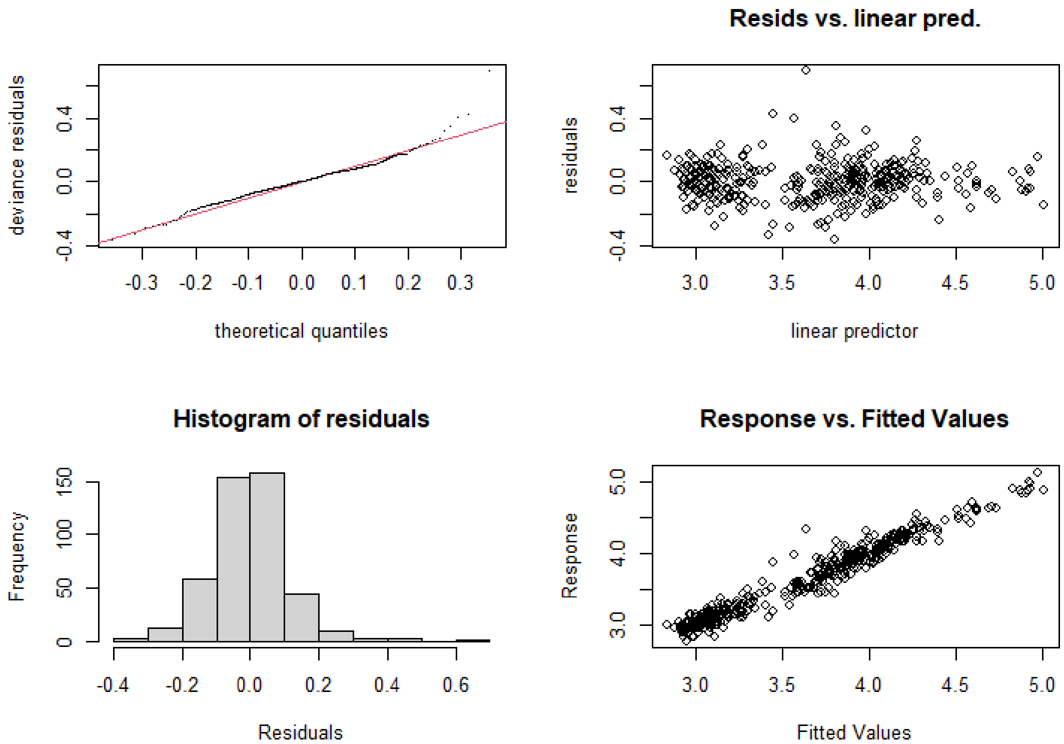

Fig.B.5 Model fitness for the rental market in eastern region

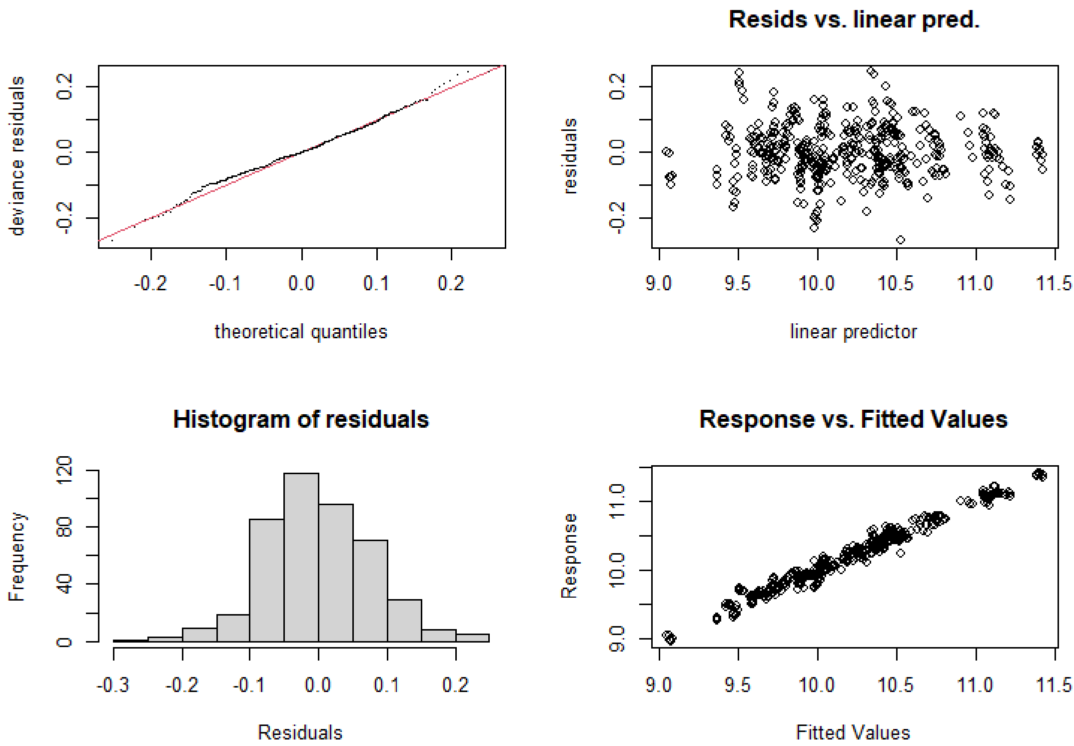

Fig.B.6 Model fitness for the sale market in eastern region

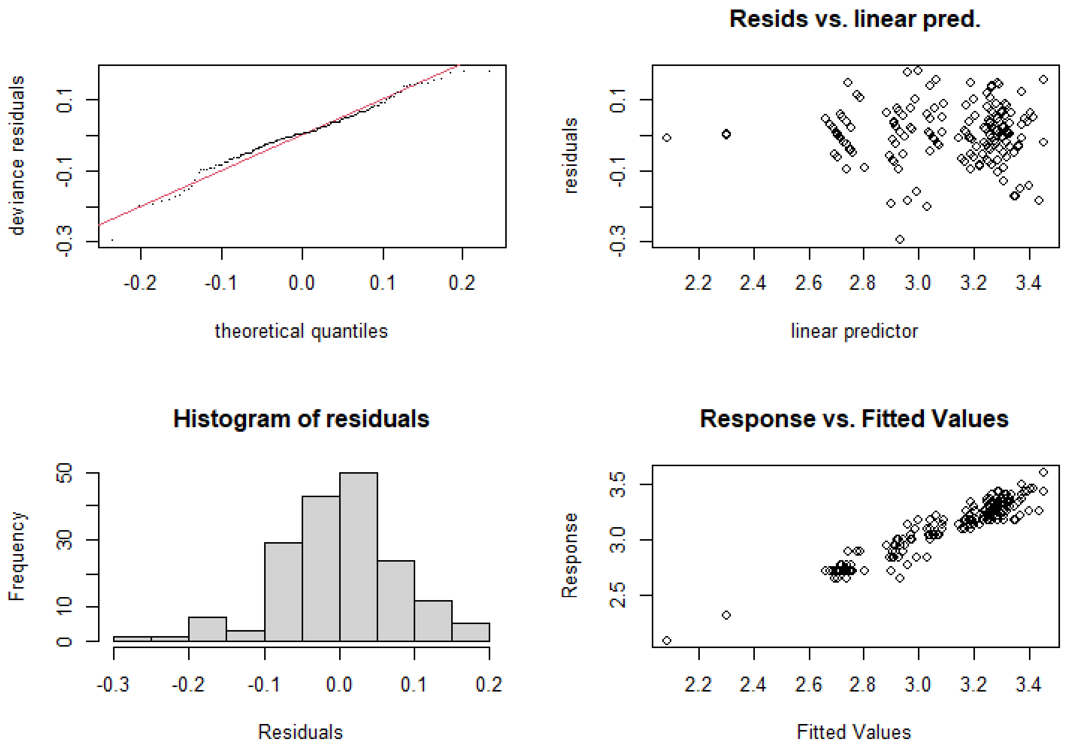

Fig.B.7 Model fitness for the rental market in central and western regions

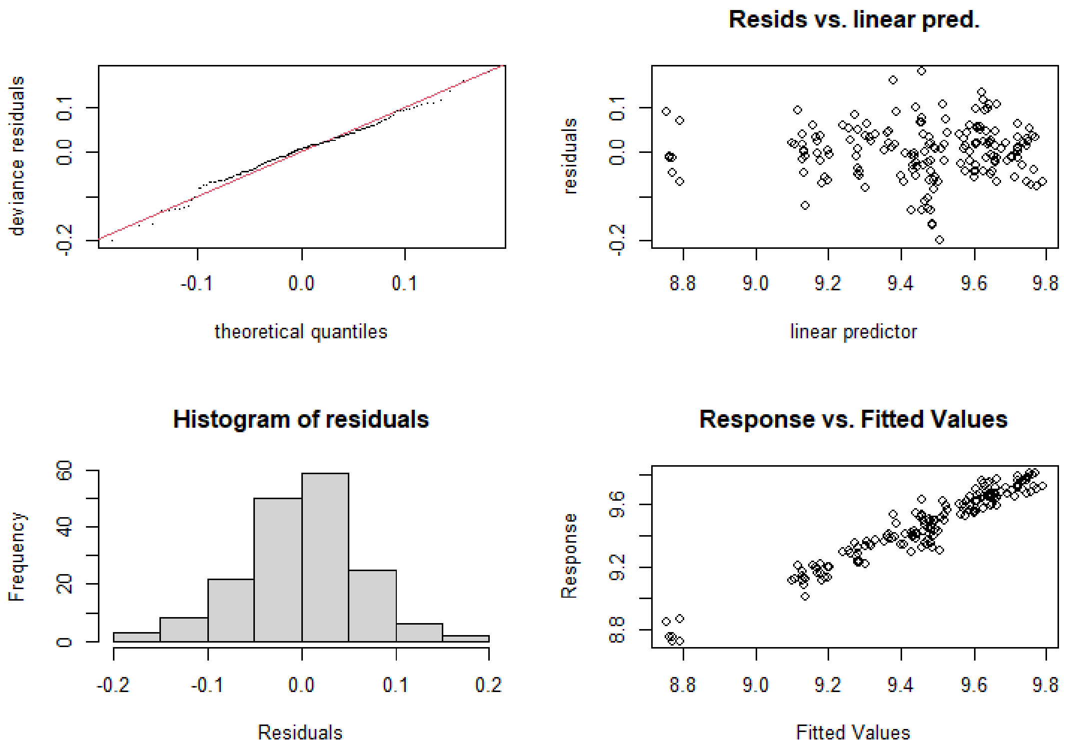

Fig.B.8 Model fitness for the sale market in central and western regions

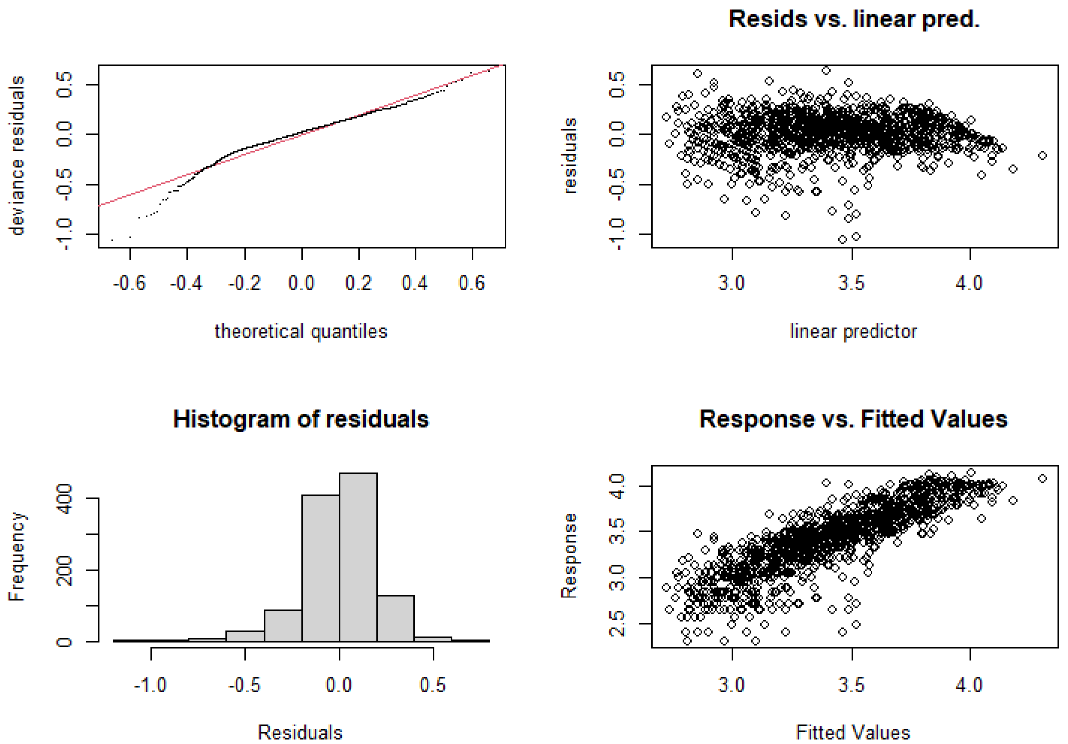

Fig.B.9 Model fitness for the rental market in northeastern region

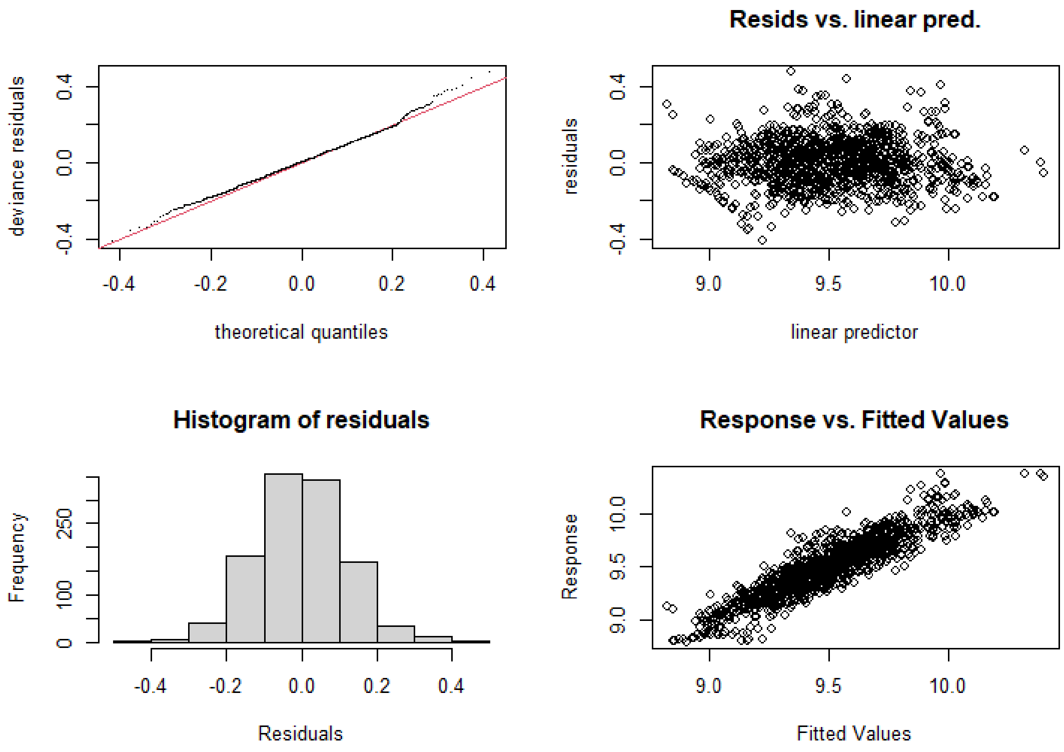

Fig.B.10 Model fitness for the sale market in northeastern region

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