The Impacts of Gasoline Stations on Residential Property Values: A Case Study in Xuancheng, China

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Abstract In this paper, we examine the effect of gasoline stations on residential multifamily housing prices in Xuancheng, China. First, a survey examining beliefs and the Not in My Backyard (NIMBY) issues associated with gasoline stations investigated the public attitude toward the impact of gasoline stations. The results show that, although the gasoline stations have adopted advanced safety management, 86% of people believe that they will decrease nearby housing prices. Second, in March and April 2016, a hedonic pricing model was used to measure the impact of gas stations on the sales’ prices of 601 residential units in 22 multifamily neighborhoods that are up to 1,000 meters from the gas stations. The results show that housing prices increase significantly with every additional kilometer from the nearest gasoline station, and the closer to the gasoline station that the house is, the more negative the impact on the housing price. The closest 100-meter band showed almost a 16% reduction in housing price, and the furthest affected band (301–600 meters) was down by almost 9%. The negative effect was not observed at distances beyond 600 meters.

The Not in My Backyard (NIMBY) phenomenon is a situation where one or more members of a community oppose the establishment of an inherently undesirable project (such as a hazardous waste dump or radioactive material storage) too close to their homes, for fear of potential negative consequences. In the early 1970s, many scholars in the United States began to study the negative effect of NIMBY facilities, such as landfills, power plants, prisons, and airports, and achieved useful results. However, in China, although many NIMBY facilities exist, little research has been done on estimating the price effects.

A gasoline station is a type of NIMBY facility; these stations store hazardous substances, such as petroleum, in underground tanks, and they are also power supply stations for cars and other motor vehicles. In recent years, the number of gasoline stations has been increasing quickly, along with the number of motorized vehicles in China. Data show that, by the end of 2013, there were approximately 96,313 gasoline stations in China, with the density being up to 4.48 stations for every hundred kilometers.¹ Over time, the gas station storage tanks may leak, due to corrosion, cracks, defective construction materials, and spills during refilling.
and maintenance activities. Petroleum pollution from leaking underground storage tanks (LUSTs) contaminates the surrounding soil and local groundwater aquifers and damages the associated watershed and ecological systems. According to the news report on an industrial information website, in China there has been no authoritative investigation into LUSTs from gas stations. In addition, the Control Standards of Leakage Pollution for Gasoline Filling Stations is still at the opinion stage.

Due to the potential environmental and human health risks, gasoline stations may have negative effects on the surrounding neighborhood. This study, therefore, contributes to the literature in China and adds to the growing body of literature on the externality effect of NIMBY facilities. First, we employed a questionnaire survey of residents to examine the beliefs and the NIMBY issues associated with nearby gasoline stations. Then, we use the hedonic price valuation method to determine the cost of this externality. Hedonic methods attempt to identify the price effect associated with each of the factors that affect price, including proximity to a NIMBY facility. The price impact on nearby property values is then used as a measure of welfare loss resulting from the NIMBY facilities.

This paper is organized as follows: First, we review the academic literature regarding the impact of undesirable facilities on property values. Next, we present the findings of a survey that was conducted to understand residents’ cognition on the influence of nearby gasoline stations, especially the effect on housing prices, together with the results of an interview with gasoline station managers to understand the measures taken by gasoline stations to reduce the NIMBY effects. Then, we describe a residential transaction data set of 601 observations that we utilized. We next present several hedonic pricing models utilizing the neighborhoods within one kilometer of a gasoline station in March and April 2016. Tests were conducted to determine a price effect of gasoline stations on surrounding property values and the extent of this effect. This study can provide government and developers with the information needed to establish some timely compensation measures to manage the NIMBY effect and will help residents to understand the NIMBY effect more rationally and make a more reasonable estimation of the NIMBY effect on property values.

**Literature Review**

Conventional theory, operationalized by hedonic regression (Rosen, 1974), holds that the value of a house is determined by its characteristics, including neighborhood amenities and disamenities. Thus, proximity to an undesirable facility should be reflected by a price that is lower than that of an identical house that is not near such a facility, holding all else constant. Hedonic price models have long been used to evaluate not only the physical attributes of housing units (e.g., square footage, number of bathrooms, and air conditioning) but also the surrounding environment and locational amenities (e.g., local school quality, crime rate, and air quality). Many studies have evaluated the effect of hazardous or undesirable facilities on nearby real estate; such studies include the following: waste sites (Kohlhase, 1991; McCluskey and Rausser, 2001; Ihlanfeldt and Taylor,

Valuation of Gas Stations Externalities Studies

Studies in this literature examine the effects of oil or gas pipelines: whether being close to a pipeline alone affects the sales price of residential properties; the direct effect of a pipeline rupture on the values of residential properties; and the effect of a pipeline rupture on properties that do not experience contamination but are proximate to the affected pipeline.

Robert Simons conducted a series of studies on the effects of pipelines that typically carry petroleum products like gasoline, fuel oil, and natural gas. Simons, Bowen, and Sementelli (1997) found a property value loss of 17% in the case of close proximity (same block or within 300 feet) to LUST sites where the site still had tanks in place. Simons and Sementelli (1997) found that non-contaminated, easement-holding properties not directly contaminated by a petroleum pipeline rupture sustain a loss in value. This reduction, attributed to the expectation that another rupture may occur, indicates a 5.5% loss in sales’ price for single-family homes and a 2% to 3% loss for multifamily units. The research also shows that a price reduction continues for several years after the event. Simons (1999) also conducted case study research on the effects of a long-term pipeline leak on a residential neighborhood in Summit Count, Ohio. The long-term petroleum leak that caused localized groundwater contamination in this rural area was found to decrease residential property values upon resale by more than 25%.

Another pipeline study by Simons, Mikelbank, and Winson-Geideman (2001) considered a pipeline spill along the Patuxent River in Maryland where petroleum on its way to a power plant was released into a river and traveled as far as 10 miles away, both upstream and downstream, on both banks of the river. Both hedonic and predictive regression models were used. Approximately 2,300 home sales were examined. The results showed that there was a statistically significant loss in sales’ price of approximately 10% in the first sales’ year.

Hansen, Benson, and Hagen (2006) used a hedonic price model to estimate the effect of proximity to two major fuel pipelines running parallel through suburban areas in Bellingham, Washington. The results showed that proximity to a pipeline is not statistically significant. Fruit (2008) studied the effects of both the announcement to construct and the 2004 completion of a 62-mile long gas pipeline on the sales’ prices of residential single-family properties in Clackamas and Washington counties in Oregon. The author found no negative effect of the gas pipeline on nearby property values. Neither study found support for the effect of proximity to a pipeline on property values.

Boxall, Chan, and McMillan’s (2005) study, which analyzes the effects of oil and natural gas facilities on rural home values in Alberta, Canada, generated mixed
results. They found that home values up to four kilometers away are, on average, 4% to 8% lower, all else being constant. This effect depends on both health risks and other undesirable features posed by nearby facilities. However, the number of nearby underground gas pipelines does not significantly affect property values; perhaps because they are underground and relatively unobtrusive.

Most of the studies above examine the effect of single-family dwellings, and few studies have focused on the effect of condominiums. Winkler and Gordon (2013) used a hedonic pricing model to study the effect of the Deepwater Horizon oil spill on waterfront condominium sales’ volume in impacted areas in Alabama. The results showed that there was a 50% decline in sales volume in the six months following the spill. Prices declined 7% in the six weeks following the spill and increased 8.8% in the following two months. The impact was not significant after the well was capped. Siegel, Caudill, and Mixon (2013) also studied the same case. They found that the spill resulted in a temporary price decrease of $21–$28 per square foot and that the price effect dissipated after three months.

These studies clearly show that pipeline ruptures, resulting in leaks, spill explosions, and environmental damage, unambiguously lower the value of affected properties in the immediate aftermath of the event. Only a small number of studies have reported that there is no obvious evidence that the presence of a pipeline, whether gas or oil, decreases estimated property values. In these studies, transaction prices were uncorrelated with the distance to a pipeline if there was no recent spillage incident; the studies did not separately either identify or estimate the effect on properties with a pipeline easement. Thus, in this paper, we examine the effect of a pipeline easement on the market value of residential properties using a hedonic price model.

**Externality Research Papers in China**

With respect to Chinese property markets, although there are numerous articles on the effect of various factors on real estate prices, the peer-reviewed literature focuses on the valuation of positive effects, such as green space, a subway, views, and schools. The residential housing examined in China typically refers to high-rise condominiums.

Jiang (2006) used a non-parametric regression model to assess the price of housing around West Lake in Hangzhou. The author found that every 1% increase in distance from the house to the lake led to a value decrease of 16.4%. Shi and Zhang (2010) applied the hedonic pricing method (HPM) to analyze the effects of Huangxing Park in Shanghai on the surrounding residential prices, and the results showed that the maximum impact radius was 1.6 kilometers, and the strongest impact location was within 0.3 kilometers. Nie, Wen, and Fan (2010), using the case of Shenzhen Metro Line Phase 1 and the HPM statistical method, quantitatively analyzed the spatial and temporal effect on surrounding property value from 2001 to 2007. The results showed that the transit line had a positive spatial effect on the property value within a radius of 700 meters around stations. The property value increments within the radius of 700 meters and 100 meters were 19.5% and 37.8%, respectively.
However, almost none of the studies on the property market in China address the negative property value effects that may be produced by industrial factories, waste sites, landfills, or incinerators. Further, the only papers are qualitative impact studies, such as whether the contamination had an effect on price. Wang (2005) provided a way to analyze the effect of gasoline stations on surrounding houses by introducing the methods and steps of valuation of real estate, but the author did not analyze actual cases. Zhang (2007) studied residential units affected by electromagnetic fields and collected sales price, second-hand housing price, and rental price data to make a comparison with Beijing housing price changes over the same period. The results showed that these facilities can affect the long-term sales’ prices through stagnation, or even decline, and that sales’ prices fluctuated with media reports. Further, pollution controls reduced the negative effects on sales’ prices. However, Zhang only uses a comparison method to value the extent of the effect.

Zheng (2009) estimated the economic value of clean air in Beijing. The results showed that a decrease of 1 microgram per cubic meter in total suspended particulate (TSP) was associated with a 0.93% increase in property values. Chen and Hao (2013) analyzed residents’ negative willingness to pay for waste transfer stations based on a study of spatial difference for 25,200 second-hand house prices in Shanghai. They found that the housing price dropped 3.6% for each kilometer that the houses were closer to the waste transfer station. Zeng, Chen, Miao, and Liu (2014) explored the impacts of contamination on the price of adjacent land based on a study of 515 auction plots of land between January 2001 and May 2013; 14 of the plots were adjacent to the contaminated land. The results showed that contamination resulted in a 31% net loss of land value. The dependent variables included the land area, the land price, the plot ratio, and the land grade.

Zhao, Simons, and Fan (2016) and Zhao, Simons, and Zhong (2016) conducted studies using a hedonic price model. Zhao, Simons, and Fan examined the effects of the Nengda municipal incineration plant in Hangzhou on residential property values. A hedonic pricing model was employed to examine the sales of more than 500 residential condominium units in more than 20 multifamily buildings within ten kilometers of the incineration plants over a one-year-period, 2014. The results showed that proximate properties showed decreases of up to 25.9% in their initial listing prices, declining monotonically until the effect was not identified at three kilometers from the incinerator. Zhao, Simons, and Zhong employed hedonic price modeling for 2,200 residential transactions in more than 70 multifamily buildings within ten kilometers of the incineration plants over a one-year period, from 2014 to 2015. The results showed that the neighboring properties showed decreases of up to 25% in the initial listing price, declining until the effect was not identified, at approximately three kilometers from the incinerator. The most consistent losses were approximately 10%, at 1–2 kilometers from the nearest incinerator.

Thus, with respect to negative externalities on residential property values in China, there is a lack of quantitative research on how to value the effect, what kind of research methods should be used, and the measurement of the effect. This paper addresses these shortcomings for gasoline stations, one kind of NIMBY facility in Xuancheng, Anhui province, China.
Exhibit 1 | The Distance between the Residential Area and the Gasoline Station

<table>
<thead>
<tr>
<th>Distance to Gasoline Station</th>
<th>Neighborhoods</th>
</tr>
</thead>
<tbody>
<tr>
<td>0–300 meters</td>
<td>JZXC, JLX, MYXC, MJH, MJHY, MXY, KQFJ</td>
</tr>
<tr>
<td>301–600 meters</td>
<td>CDXC, XCJH, ECHY, JBHY, XCBZ</td>
</tr>
<tr>
<td>601–900 meters</td>
<td>MDXC, BL, JTSZ, DFYY, XJJJ</td>
</tr>
<tr>
<td>&gt;901 meters</td>
<td>ZRC, MZSC, SJHY, WLJ, YLW</td>
</tr>
</tbody>
</table>

Study Area

Xuancheng is a national demonstration zone undergoing industrial refurbishment and it is located in southeast Anhui province. The south and southeast regions are in the Tianmu Mountain range, while the southwest and west regions are parts of the Mt. Huangshan and the Mt. Jiuhua ranges, respectively. Xuancheng consists of Xuanzhou District, Ningguo City, and five counties: Langxi, Guangde, Jixi, Jingxian, and Jingde, having an area of 12,340 square kilometers and a population of 2.79 million at the end of 2015.

In this paper, the study area mainly refers to Xuanzhou District. The total area of Xuanzhou District is 2,533 square kilometers, and it has a total population of 868,000. At the end of 2014, the number of private motorized vehicles was 173,609, and there were almost 50 gasoline stations. Exhibit 1 shows the location of nearby residential neighborhoods, while Exhibit 2 shows the locations of gasoline stations in Xuanzhou District.

Attitude of Residents to Gasoline Stations and their Safe Management

Our investigation consisted of two phases. The first phase was an interview of gasoline station managers conducted in Xuanzhou District in April and May 2016. We randomly interviewed managers of two gasoline stations according to the interview outline. The second phase was a questionnaire survey. The survey respondents were people who lived within 1 kilometer of gasoline stations; only 126 agreed to participate in the survey. The survey was conducted in April and May 2016. In the investigation, questionnaires were randomly given to residents to answer on site and were then taken back for SPSS analysis of the data.

Best Practice of Gasoline Stations Safety Management

The interviews of gasoline station managers in Xuanzhou District were conducted to understand whether they have adopted any measures to eliminate the effects of NIMBY. The contents and answers of the questionnaire are as follows: The safety management guidance system used in gasoline stations is the most advanced Health Safety and Environment Management System, given that it includes...
quality, safety, production, and environmental protection. The permit effectively ensures that a gasoline station can meet national safety standards. The managers also implemented the safety regulations to control known risk factors, such as explosions, corrosion of underground storage tanks, and other problems, including staff pre-job training. Security managers carry out pre-and post-job safety checks every day and conduct a thorough check once a week; the oil company also
conducts a regular inspection of all gasoline stations. The oil company is greatly concerned with the life and health of the employees. It implements occupational disease prevention measures, including an annual physical examination, to protect the employees and regularly inspects various factors that may damage the gasoline station.

We believe that the gasoline stations are convenient for customers, and offer fueling and shopping options. The gasoline stations have not received any complaints from nearby residents.

**Resident’s Attitude to the Effect of Gasoline Stations on Housing Price**

The purpose of our investigation is to understand both the attitudes of residents who live at different distances from gasoline stations and their perceptions of the impact of a gasoline station on housing prices. We developed a questionnaire, based on the literature, to identify the factors that influence gasoline stations and their effect on the prices of nearby homes. Exhibit 3 provides the survey questions.

The survey includes questions on participant characteristics (gender, age, residential areas); perception of the influencing factors from gasoline station (fire and explosion, noise pollution, atmosphere, soil and water pollution problems); willingness to live near a gasoline station (yes or no); awareness of the impact of gasoline stations on nearby housing prices (positive effect, no effect, and negative effect); the impact of gasoline stations on the prices of nearby homes (5% or less, 6%–10%, 11%–15%, more than 16%).

Ultimately, 126 valid questionnaires were collected from April 28, 2016 to May 6, 2016. The data obtained from the questionnaires and the questionnaire’s
reliability were assessed using Cronbach’s alpha; the figure obtained was 0.96, indicating that variance in the score is explainable. We adopted a descriptive analysis and a cross analysis, using SPSS software, to study the residents’ attitudes regarding the effects of gasoline stations on housing prices.

Exhibit 4 shows that 39% of the 126 survey respondents were women and 61% were men. Respondents aged less than 25 years old accounted for 9% of the total, those between 26 and 35 years old accounted for 18%, those between 36 and 45 years old accounted for 22%, and those who were older than age 46 accounted for 51%.

Exhibit 5 shows that, among the many effects of the gasoline station, 48% of respondents believed that gasoline is a dangerous substance that is flammable and can be explosive; thus, they thought that the potential risk of explosion could have a significant impact on nearby house prices. Approximately 24% of respondents believed that vehicle noise pollution has the greatest impact on nearby residents,
while 17% believed that the positive externality of gas stations lies in their convenience, such as their fuel and shopping options.

Exhibit 6 shows that 92% of respondents said that they did not want to live near a gasoline station and 86% thought that a gasoline station would reduce the prices of nearby houses. But when asked to assess the housing prices due to the nearby gasoline station, most said they do not know how much the influence would be. And the percentage of answers for each option was basically the same, with the answer being close to the middle option “6%~10%,” indicating that respondents did not know how great the impact of a gasoline station was on the prices of the surrounding housing.

We found that, although the gasoline stations may adopt advanced management methods to reduce risks, most respondents believed that they exhibit a strong NIMBY effect. Nearly 90% of respondents believed that house prices will decrease due to a nearby gasoline station, but the level of influence is unknown. From the perspective of the oil companies, avoiding the NIMBY effect is the government’s mandatory requirement, and the companies themselves also want to avoid this kind of effect as far as is possible. Thus, in the following section, we adopt the hedonic price model to address the impact of a gasoline station on the values of nearby properties.

### Residential Transaction Data Set and Models

A hedonic price model is the standard approach to estimating the effects of externalities on residential property value. Our analysis of residential property sales employed a standard hedonic regression technique (Rosen, 1974; Simons, Robinson, and Lee, 2014). The dependent variable is the sale price, and the independent variables include several housing-related control variables. Vectors of independent factors include housing characteristics (typically for stacked-flat condominium sales), location, neighborhood characteristics, and proximity to a gasoline station, measured in various ways, including the distance rings approach. The model takes the form:

\[
HP = \beta_0 + \beta_1 HC + \beta_2 LOC + \beta_3 GS + \varepsilon, \tag{1}
\]

where $HP$ is the initial listed sales’ price of each condominium unit sold, in either linear or log form; $\beta_0$ is the model intercept; $HC$ is a vector of housing characteristics, including livable floor area, number of bedrooms, living rooms, and bathrooms, floor, a high-rise dummy, decoration, and age at date of sale; $LOC$ is a vector of proximity variables for distances to CBD (Xuancheng government center) and the nearest shopping mall, school, park, etc.; $GS$ is the distance of the home from the nearest gasoline station, measured either in distance or in 1-kilometer distance rings, as discussed below; and $\varepsilon$ is the error term.

In general, in China data on second-hand (resale) housing transactions are difficult to obtain directly from government offices. Online data of second-hand for-sale
**Exhibit 6** | Residents Attitudes and Perceptions of the Gasoline Stations Effect on House Prices (n = 126)

<table>
<thead>
<tr>
<th>Distance</th>
<th>Respondents</th>
<th>Willingness to Live near Gasoline Station</th>
<th>Effect of Gasoline Station on House Price</th>
<th>Range of Gasoline Station Effect on House Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Yes</td>
<td>No</td>
<td>Positive Effect</td>
</tr>
<tr>
<td>0–300 meters</td>
<td>34</td>
<td>5</td>
<td>29</td>
<td>0</td>
</tr>
<tr>
<td>301–600 meters</td>
<td>31</td>
<td>1</td>
<td>30</td>
<td>0</td>
</tr>
<tr>
<td>601–900 meters</td>
<td>31</td>
<td>1</td>
<td>30</td>
<td>1</td>
</tr>
<tr>
<td>&gt;901 meters</td>
<td>30</td>
<td>3</td>
<td>27</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>126</td>
<td>10</td>
<td>116</td>
<td>1</td>
</tr>
<tr>
<td>Percentage</td>
<td>100%</td>
<td>8%</td>
<td>92%</td>
<td>1%</td>
</tr>
</tbody>
</table>
housing listings are generally transparent and available in real time, but actual transaction prices are generally not readily available. The housing resale listings data collected for this paper come from “listings to sell” on http://hz.58.com/.

Among the independent variables, according to research by Wen (2004), the “living level” dummy variable is equal to the sum of five categories, including grocery, supermarket, bank (only including four state-owned banks), post office, and hospital (including hospital, clinic, health service station) within 1,000 meters, and each category is equal to 1 if yes, and 0 otherwise. The “education level” is a dummy variable equal to the sum of four categories, including kindergarten, primary school, middle school, and college in the neighborhood and each category is equal to 1 if yes, and 0 otherwise. “Buslines” is defined as the number of bus lines within 500 meters. The distances for all locational variables, including to the nearest gasoline station, come from an electronic map (http://map.baidu.com). The authenticity and validity of these data are of high quality, and they are generally accepted as being accurate.

We use original list prices for residential condominium transaction data sold in March and April 2016. Second-hand (resale) housing transactions come from published information of the private real estate agency, cleaned of duplicate sales. As mentioned earlier, residential listing prices were obtained at http://hz.58.com/. This yielded 601 transactions.

Exhibit 7 contains descriptive statistics for our housing transaction data set. The typical unit in our data set had 2.81 bedrooms, 1.9 living rooms, 1.26 bathrooms, was on the 6.1th floor, and was 12.52 years old at the time of sale. The typical unit measured 104.18 square meters in size and was listed at ¥576,700 prior to sale. The living level was approximately 4 scores, and the education level was approximately 2.6 scores, on average. The distance to CBD was typically 1,562 meters; the distance to a park was 944 meters; and the distance to the nearest gasoline station was 659 meters.

Model Results

Baseline Model

After investigating the broad classes of models (linear, semi-log, and log), and comparing the goodness-of-fit criteria across the three model specifications, a semi-log form offered the best fit as a dependent variable for this study. The results of the first baseline model are shown in Exhibit 8. This model examined 601 condominium sales, and the dependent variable was the list price.

For the baseline model presented in Exhibit 8, the adjusted $R^2$ (reflecting the amount of variation in the dependent variable explained by all the independent variables combined) is 79.3%; in addition, the F-statistic is 167.79 and the Durbin-Watson statistic is 1.72, figures that are also highly satisfactory. The current model has tolerable levels as the variance inflation factor (VIF) for all variables is below 10. Exhibit 8 has a dozen independent inflation variables, as described earlier, and shows the key variable of interest: distance to the gasoline station in meters.
Exhibit 7 | Descriptive Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>List Price</td>
<td>Listing price (10,000 yuan)</td>
<td>28</td>
<td>120</td>
<td>57.67</td>
</tr>
<tr>
<td>Unit Area</td>
<td>Area (m²)</td>
<td>33</td>
<td>240</td>
<td>104.18</td>
</tr>
<tr>
<td>Age</td>
<td>Age at sale</td>
<td>6</td>
<td>23</td>
<td>12.52</td>
</tr>
<tr>
<td>BR</td>
<td>Bedrooms</td>
<td>1</td>
<td>6</td>
<td>2.81</td>
</tr>
<tr>
<td>LR</td>
<td>Living-rooms</td>
<td>1</td>
<td>4</td>
<td>1.91</td>
</tr>
<tr>
<td>BA</td>
<td>Bathrooms</td>
<td>1</td>
<td>3</td>
<td>1.26</td>
</tr>
<tr>
<td>Decoration</td>
<td>Dummy for level of finish (1-rough, 2-common, 3-good,</td>
<td>1</td>
<td>5</td>
<td>2.64</td>
</tr>
<tr>
<td></td>
<td>4-great model, 5-luxury model)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Floor</td>
<td>Floor</td>
<td>1</td>
<td>33</td>
<td>6.10</td>
</tr>
<tr>
<td>Dummy–High-rise</td>
<td>High-rise (≤ 6 floor = 0, 7 &lt; floor ≤ 9=1, &gt; 10 = 2)</td>
<td>0</td>
<td>2</td>
<td>0.77</td>
</tr>
<tr>
<td>Living level</td>
<td>Dummy variable equal to the sum of five categories,</td>
<td>1</td>
<td>5</td>
<td>4.01</td>
</tr>
<tr>
<td></td>
<td>including grocery, supermarket, bank, post office and</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>hospital within 1,000 meters, and each category equal to 1 if yes, 0 otherwise.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education level</td>
<td>Dummy variable equal to the sum of four categories,</td>
<td>1</td>
<td>3</td>
<td>2.60</td>
</tr>
<tr>
<td></td>
<td>including kindergarten, elementary school, and middle school within 1,000 meters, and each category equal to 1 if yes, 0 otherwise.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance–Park</td>
<td>Distance to the nearest park (m)</td>
<td>150</td>
<td>2150</td>
<td>944.31</td>
</tr>
<tr>
<td>Buslines</td>
<td>The number of bus lines within 500 meters</td>
<td>0</td>
<td>10</td>
<td>3.25</td>
</tr>
<tr>
<td>Distance–CBD</td>
<td>Distance to CBD</td>
<td>420</td>
<td>3110</td>
<td>1562.10</td>
</tr>
<tr>
<td>Distance–Gasoline</td>
<td>Distance to the nearest gasoline station (m)</td>
<td>50</td>
<td>1590</td>
<td>659.13</td>
</tr>
</tbody>
</table>

We adopted the stepwise method to run the model. Exhibit 8 shows that there were eight independent variables of 14 variables stepped into the model at the 99% level of confidence; these include the unit area, age at sale, decoration, floor, the high-rise, distance to CBD, and distance to gasoline station. Among the eight variables, the area size, decoration, high-rise, and distance to gasoline station showed a positive effect on house price, while the other variables exhibited a negative effect. In the basic model, the standardized regression coefficient of linear regression was directly related to the hidden price.

The independent variables typically found in a hedonic regression model conformed, for the most part, to expectations (see Exhibit 8). For example, unit area (0.007, or a 0.742% increase in list price for each additional one square meter), living-rooms (0.049, or a 5.02% increase in list price for each additional living-room), decoration level of finish (0.040, or a 4.046% increase in list price for a higher level of decoration on an index scale) were statistically significant at a 99% level of confidence, and high-rise (0.023, or a 2.35% increase in list price for an additional level of high-rise). Age (−0.010) and floor (−0.005) were negative and significant at a 99% level of confidence, as expected. We assume that better
views from higher floors are not important enough to offset the inconvenience of additional height and greater density.

Housing prices moved significantly down the further the properties were from the Xuancheng CBD, at a rate of 0.014% per meter; and, with respect to distance to the nearest gasoline station, moving further away from the station was associated with an increased list price, at a rate of 0.018% per meter, holding all other variables in constant. This was statistically significant at a 99% level of confidence. Thus, consistent with theory, we conclude that proximity to a gasoline station has a negative effect on property value, but the variable specification (in distance per meter) does not provide information on how far the effect may extend. This is addressed in the next model.

**Distance Rings from Gasoline Station Model**

This model can be estimated in two ways. One model is a separate regression for each of the distance rings, while the other is a model estimated over the entire sample, with interaction terms of distance and time period indicators to measure the changing impact of the nearest negative disamenity (Gamble and Dowing,
1982; Kohlhase, 1991; Kiel and McClain, 1995). We adopted the second approach. Dist 1, Dist 2, Dist 3, Dist 4, Dist 5, and Dist 6 represent the neighborhoods located at 0–100 meters, 101–200 meters, 201–300 meters, 301–600 meters, 601–900 meters, and >901 meters, respectively.

The results of the distance rings model are shown in Exhibit 9.

This model also examined 601 sales, and the dependent variable was, likewise, the natural log of the list price. The adjusted $R^2$ was 0.81, the F-statistic was 204.728, and the Durbin-Watson statistic was 1.746, all of which are highly satisfactory. The model also had tolerable levels of VIF for all the variables. The same dozen or so independent variables were included, with generally similar results.

The only substantial difference in the models was the key independent variable of interest, distance to the nearest gasoline station, which was expressed in a series of dummy variables of 1,000-meter bands. The results showed that the effect of proximity to any of the gasoline stations on the list prices could be measured, holding all the other variables in the model constant. Within 600 meters of the nearest gasoline station, the coefficient for the corresponding variable showed a negative effect related to the nearest gasoline station: within 100 meters, the coefficient was $-0.181$, or an estimated loss of 16.6%\(^8\) (Halvorsen and Palmquist, 1980); between 101 and 200 meters, the coefficient was $-0.201$, for an estimated loss of 18.2%; between 201 and 300 meters, the coefficient was $-0.071$, for an estimated loss of 6.8%; between 301 and 600 meters, the coefficient was $-0.094$, for an estimated loss of 8.9%; between 601 and 900 meters, the coefficient exhibited a positive effect to the nearest gasoline station, with an estimated increase of 2.8%. Thus, we conclude that a gasoline station has a negative effect on property values within 600 meters.

### Spatial Autocorrelation Analysis

House price data are often spatially correlated. That is, properties with high values are generally located in close proximity to other properties of comparable value, and low value properties are also clustered. Thus, in this study, we are concerned...
about spatial autocorrelation. However, the residential housing units examined were all high-rise properties; thus, we only had neighborhood centroids, not the location of each transaction. So, we tested for spatial autocorrelation using Moran’s I on these 22 multifamily high rises, and the value of Moran’s I was $-0.014$, which is close to 0, and indicated less spatial autocorrelation.

The results are shown in Exhibit 10. The results indicate a potentially slight spatial autocorrelation problem. So, we replicated the classical OLS model with 22 neighborhood observations (by using average list price). The adjusted $R^2$ was 97.9%, consistent with previous models (79.3%). Of course, with a smaller $N$, the $F$-statistic was much lower (69.7), as expected. The parameter estimates on distance to the gas station were about the same, but at 0.011, not 0.014. Both are statistically significant at greater than the 95% level of confidence, so our main results remain unchanged.

For spatial autocorrelation, we compared statistics of the LM-Lag (0.54) and LM-Error (1.22) of the OLS model. As the $P$-values, they were not significant at the 90% level of confidence; thus, it was not necessary to run the spatial lag and spatial error models. In conclusion, we find that spatial autocorrelation did not affect the main results.
**Conclusion**

The main aim of this study was to examine the property value impacts of gasoline stations on proximate for-sale residential units in Xuancheng, China. We applied hedonic pricing models, with a total of 601 valid observations, where the dependent variable was the natural log of the original list price in March and April, 2016.

First, a survey of neighborhood residents’ attitudes to nearby gasoline stations and an interview of gasoline station managers showed that almost 90% of the residents believe that a gasoline station has a strong NIMBY effect, the reason being that most of the residents were not fully aware of the safety management measures of these stations and also lacked relevant knowledge of the NIMBY effect. A total of 86% of residents believed that a gasoline station would decrease the prices of nearby houses, but they did not know the extent of such a decrease. Secondly, a hedonic price model was constructed. The results showed that the presence of a gasoline station had a statistically significant negative effect on the value of residential properties within 600 meters, with the closest 100-meter band showing an almost 16% reduction in house prices and house prices in the furthest affected band (301–600 meters) declining by almost 9%.

The results can help real estate developers make comprehensive pricing decisions, both in acquiring development sites and in pricing units for sale, therefore potentially leading to fairer prices and more efficient markets. The models also provide parameter estimates for regional accessibility, traffic conditions, schools, transit, and other proximate factors. For local government, since gasoline stations are a component of local public services, the efficiency of housing markets would be improved if negative externalities attributable to public services can be internalized. Thus, residents could be “made whole” (be free of damage). This research would give city governments the opportunity to create considerably more rational urban planning policies.

**Endnotes**

3. Ningguo is a county-level city under the jurisdiction of the province, and entrusted by Xuancheng.
4. The number of gasoline stations can be estimated based on the number of motorized vehicles in the city, that is, there are a certain number of vehicles per gas station. And the empirical data indicate approximately 2,500–4,000 vehicles per station. Thus, according to the number of private vehicles and gasoline stations in Xuanzhou District, we can calculate the average level in the District. There are 3,470 vehicles per gas station, which is the average level.
5. In a study on the stability of the list–sales price ratio, Haizhen (2004) analyzed the relation between the list price of a house and the transaction price, based on 270 list–sales price pairs in Hangzhou in 2004. The author found a significant linear relation,
with transaction price = \(-1.196 + 0.930 \times \) listing price, relative to the Chinese housing market. A bivariate plot indicated that the adjusted \(R^2\) reflecting the relation between list price and transaction price was 0.983, which was very close. Further, the variance of the residuals of cumulative probabilities of the observations and the expected cumulative probability is normally distributed (Wen, 2004, p. 67). The use of Haizhen’s list–sales price transformation has been used previously in the Chinese real estate literature. For example, Wu, Guo, and Chen (2008) analyzed the impacts of lakes and landscaping on residential house values in Nanjing, and used list price as the dependent variable in a hedonic price model. As with the current case, it was acknowledged that using sales price was theoretically better, but that reliable sales price data were difficult to obtain. The potential magnitude of error in using of the listing data was minimal, as there was a correlation coefficient 0.97 (list–sales) based on a data set of sales from 2006 for Nanjing (the sample size was 49). In China today, the homeowner/sellers’ online list price reflects the anticipated price to the seller in a competitive market with acceptably complete information. Hence, list prices may be more sensitive to market fluctuations, and they are often considered more capable of reflecting the true market value (Pollakowski, 1995). Also, according to a Southwest University of Finance June release of “Chinese household financial survey report of 2012,” the relationship between Chinese families’ self-reported prices and market price is 95%, indicating that self-reported home prices and market prices are closely related. Further, Hao (2014) investigated the level of residential segregation in 2010 in Shanghai and its impacts on neighborhood house prices. List price was used as the dependent variable in this hedonic price model. The author pointed out that ideal second-hand housing prices should be the actual transaction price, but because of China’s real estate transfer tax, with related capital gains tax liability, the reliability of actual sales price may be low, as chattels or other valuable goods or services may be transferred to the seller in a “side deal,” (off the record) to keep the registered sales price low and, thus, minimize, the transfer tax. The author’s conclusion was that residual sales prices tend to be systematically underestimated, consistent with Wu, Guo, and Chen (2008).

6 Percentage log transformation of dummy variables, \([\exp (0.007) - 1] \times 100 = 0.7025\%\), repeated again below.

7 This variable is a reference category.

8 Percentage log transformation of dummy variables, \([\exp (-0.091) - 1] \times 100 = -16.6\%\), repeated again below.

References


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