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An empirical study of the impact of vehicular traffic and floor level on property price

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A B S T R A C T

Urban road traffic often generates noise and air pollution, thereby resulting in a disamenity effect on surrounding residential property and subsequently affecting the willingness to pay of homebuyers. Given that the distribution of road-traffic externalities varies in vertical space, heterogeneous effects of road traffic result on properties situated in different floors. Based on data of 7590 multi-story and 4980 high-rise residential properties in Hangzhou, China in 2017, this study constructs hedonic price and spatial econometric models to investigate the relationship among road-traffic externality, floor level, and property price. Empirical results show that road- traffic externalities have a significant disamenity effect on property price. Different from existing studies, we find that the floor level has a significant moderating effect on the disamenity effect of road traffic. In particular, effects on different submarkets reveal that capitalization rate is non-monotonic in vertical space and different in multi-story and high-rise buildings. Previous literature has largely ignored these issues, but the latter is crucial in estimating the influence of road-traffic externalities on property price.

Keywords:
Road-traffic externality
Property price Floor level
Moderating effect
Vertical heterogeneity
Spatial econometric model

1. Introduction

Urban road is an important part of the city transportation system. Its construction and improvement are highly important for improving urban quality. Owing to rapid economic growth, urbanization, and motorization, the road transport demand is increasing rapidly. However, road traffic generates a variety of negative externalities, such as noise, congestion, and air pollution, which have become the main traffic problems requiring urgent solutions in Chinese cities.[1] The noise and air pollution resulting from road traffic have a free flow and large influence range, which affect people's daily activities while simultaneously posing a serious threat to health. The World Health Organization (WHO) has reported that air pollution can significantly increase the incidence of cardiovascular and respiratory diseases, and that traffic noise adversely affects people's physical and mental health (WHO, 2011; 2013).

As people place extra emphasis on physical health and quality of living environment, road traffic-related noise and air pollution become important factors affecting the decision-making of homebuyers. However, as an urban public good, traffic facility cannot be traded directly in a market. In addition, valuing the external effect of road traffic is difficult. Saelensminde (1999) and Wardman and Bristow (2004) utilized the contingent valuation method to quantify the willingness to pay (WTP) of consumers for reduced exposure to road traffic-related noise and air pollution. A few scholars employed the hedonic price method to value the disamenity effect of road traffic (Baranzini, Schaerer, & Thalmann, 2010; Jin & Rafferty, 2018; Theebe, 2004). Other scholars have also conducted extensive studies on this topic. For example, Larsen and Blair (2014) investigated the external effects of road traffic on different types of properties; Franck, Eyckmans, Jaeger, and Rousseau (2015) and Blanco and Flindell (2011) studied the external effects of traffic on different housing submarkets; and Hughes (1992) investigated the effects of traffic levels on property prices. However, such studies are mostly concentrated on developed western countries, but limited importance has been attached to the effect of road-traffic externalities on property prices in developing countries, especially in China.

Most existing studies construct hedonic price models using housing transaction data and demonstrate that road traffic-related noise and air pollution have significant negative effects on property values. However, the distribution of negative externalities associated with road traffic is not constant in vertical space but varies with height (Chan & Kwok, 2000; Kalaiarasan, Balasubramanian, Cheong, & Tham, 2009; Ko, 1976). Such disamenity effects on property prices may vary from floor to floor even within a building, which results in people living on the upper floors valuing road-traffic externalities differently from residents on lower floors. With the acceleration of urbanization, the supply of high-rise residential property is booming in the Chinese real estate market. Floor level considerably influences the purchasing decision made by homebuyers. However, limited attention has been paid to the effect of floor level on property prices. Previous empirical studies only used floor level as a control variable but ignored the moderating effect of floor level on road traffic disamenity. To fill this gap, the current study considers the vertical distribution variation of road traffic externality and explores the relationship among traffic externality, floor level, and property price.

In addition, as a typical type of spatial data, the spatial effects of property price have drawn wide attention from scholars over the years (Anselin, 1988; Dubin, 1998). Previous studies have proven the existing significant spatial dependence in property price in Hangzhou (Wen et al., 2017a, 2018b). To obtain unbiased and efficient estimates, the spatial dependence should be addressed with proper methods. The spatial econometric model, which can accurately reflect the spatial dependence and optimize the traditional hedonic price model, has been extensively used in the real estate field. However, few scholars have performed spatial analyses when estimating the effect of road traffic. Therefore, this study employs the spatial lag model (SLM) and spatial error model (SEM) to optimize the traditional hedonic price model and quantitatively investigate the overall effect of road-traffic externalities on property prices. This study attempts to address the following questions: (1) Does the road-traffic externality have a significant capitalization effect on property prices? (2) Does the floor level have a moderating effect on the external effects of road traffic? If so, (3) how does the capitalization rate of the road traffic change in the vertical dimension?

Compared with the previous literature, this study presents three main contributions. First, this study is the first to investigate the heterogeneity of the disamenity effect of road traffic on property prices from the vertical spatial dimension. Owing to the vertical variation of road traffic externalities such as noise and air pollution, their disamenity effects on property values may be different from floor to floor. This study rigorously explores the vertical heterogeneity of the traffic disamenity effect on property prices, providing important references for homebuyers, developers, and policy makers. Second, this study reveals the moderating effect of the floor level, providing an innovative insight to understand the relationship between road-traffic externalities and the housing market. Third, considering spatial dependency, this study utilizes spatial econometric models to optimize the traditional hedonic price model and obtain unbiased results. Although the spatial econometric model has been broadly used in the real estate field, the spatial effects have been neglected in the studies on the relationship between traffic externalities and property prices. The rest of this paper is organized as follows: Part 2 discusses related studies on road-traffic externalities and property prices. Part 3 illustrates data sources, definitions of variables, and model specifications. Part 4 provides the empirical results. Finally, Part 5 presents the conclusions.

2. Literature review

Literature regarding the external effect of road traffic on property price has been well established (Bateman, Day, Lake, & Lovett, 2001; Brandt & Maennig, 2011; Chang & Kim, 2013; Langley, 1976; Smith & Huang, 1995; Vessali, 1996; Wilhelmsson, 2000). In general, the effects of three types of transportation facilities have attracted the most attention: highways (Kim, Park, & Kweon, 2007; Nelson, 1982), railways (Beimer & Maennig, 2017; Ozdenerol, Huang, Javadnejad, & Antipova, 2015), and urban roads (Blanco & Flindell, 2011; Hughes & Sirmans, 1992). Research approaches are divided into two categories: statement preference (SP) method, such as contingent valuation (CV) method, and revealed preference (RP) method, such as hedonic price (HP) method. CV method relies on surveys to ask respondents directly about their WTP for environmental improvement (e.g., noise reduction and air quality improvement) (Galilea & Dios, 2005; Istamto, Houthuijs, & Lebret, 2014; Wardman & Bristow, 2004). As for HP method, noise and air pollution are considered disamenities, which negatively affect housing price; by combining these disamenities with other housing characteristics, HP models are constructed to measure the implicit price of road-traffic externalities (Kawamura & Mahajan, 2005; Wilhelmsson, 2000). The shortcoming of the SP method lies in the hypothesis of the respondent's answer. By contrast, the RP method is based on real market data, and the results obtained are realistic and reliable. Therefore, this study adopts the HP method, which is also a prevalent approach, to quantify the disamenity effect of road traffic on property values.

A large number of empirical studies have proven that road traffic has a negative external effect on property prices (Andersson, Jonsson, & Ogren, 2010; Szczepanska & Wasilewicz, 2015; Wardman & Bristow, 2004). Early studies focused on the effects of large-scale traffic projects. Nelson (1982) reviewed empirical studies on the effect of highway traffic on property prices in the United States and Canada and found that traffic-related noise had significant negative effects on property values. Specifically, for every 1-dB increase in noise exposure, the property price decreased from 0.16% to 0.63%. In the last 20 years, scholars have paid extra attention to traffic external effects at the micro-scale. For example, Wilhelmsso (2000) studied the road-traffic external effect on the values of single-family houses near the CBD in Stockholm, Sweden. The empirical results illustrated that a house located in a noisy neighborhood had a discount of 30% compared with a house in a quiet area. Wardman and Bristow (2004) found that the WTPs of residents for reducing traffic-related noise intensity and air pollution level in Edinburgh, Scotland, were $33.55 and $39.91, respectively. Kawamura and Mahajan (2005) conducted a study on Chicago, Illinois, showing that the price of a single-family house was expected to decrease by 0.4% for every 10% increase in street-traffic volume.

A few scholars conducted extending studies, such as comparing the effect of road-traffic externalities on properties of different types (Larsen & Blair, 2014), in different housing markets (Blanco & Flindell, 2011; Franck et al., 2015) and comparing the effect of different traffic levels on property prices (Hughes & Sirmans, 1992). Specifically, Larsen and Blair (2014), who compared the effect of road traffic on single-family houses and multi-unit properties in Ohio, U.S., suggested that traffic external effects on two types of properties were quite different. For single-family houses, a discount of 7.8% of the price was offered for a house located on arterial streets than with a house on collector streets. By contrast, multi-unit properties near arterial streets enjoyed a premium of 13.75%. Franck et al. (2015) and Blanco and Flindell (2011) found that road-traffic externalities were valued differently across regions in Belgium and the UK. Hughes and Sirmans (1992) studied the effects of different traffic levels on single-family house prices in the city and suburban region of Baton Rouge, Louisiana. For every 1000 cars addition in the average daily traffic volume, the properties within the city areas were discounted by 1.05%, while properties in the suburban areas were discounted by 0.54%.

However, most previous studies focused on external effect of road traffic on property price from horizontal dimension, while the vertical characteristics of this effect has received much less attention. In fact, floor level represents the vertical location of a property, which may significantly affect the WTP of homebuyers (Ong, Ho, & Lim, 2003; Wong, Chau, Yau, & Cheung, 2011). Previous studies estimated the price of vertical location by adding the variable of floor level in a hedonic price model, and many of them showed that the floor-level premium was positive (Baranzini & Ramirez, 2005; Chau, Wong, Yau, & Cheung, 2007; Hui, Chau, Pun, & Law, 2007; So, Tse, & Ganesan, 1996; Wong et al., 2011). Several studies further investigated how the effect of landscape on property price varied with floor level (Hui, Zhong, & Yu, 2012; Xiao, Hui, & Wen, 2019). Specifically, Hui et al. (2012) and Xiao et al. (2019) divided the whole market into a series of submarkets according to the floor level and estimated the influence of landscape attributes on different submarkets. Additionally, some interesting studies investigated the price premium (discount) of a lucky (unlucky) number floor level arose from superstition in communities with substantial Chinese populations (Bourassa & Peng, 1999; Chau, Ma, & Ho, 2001; Fortin, Hill, & Huang, 2014; Shum, Sun, & Ye, 2014). Humphreys, Nowak, and Zhou (2019) found that Chinese buyers were willing to pay 1.7% premiums for properties located on floor levels ending with 8, and 1% discounts for properties on floor levels ending with 4. Because number 8 is a lucky number whose pronunciation is similar to the word for fortune, while number 4 is an unlucky number which sounds like the word for death. However, the vertical heterogeneity of the disamenity effect of road traffic on property price has rarely been investigated.

In summary, the following aspects are worth further exploration. First, if the vertical distribution variation of noise and air pollution is considered when estimating the disamenity effect of road traffic on property price, results can be comprehensive and accurate. In recent years, substantial efforts have been made to study the vertical profiles of noise intensity and air pollutant concentration levels, but has yielded inconsistent findings. For air pollution, some studies found that the concentration level decreased with increasing height (Peng, Wang, Wang, Gao, & Lu, 2015; Wu et al., 2002). However, several studies reported there was no significant correlation between pollutant concentration and height (Morawska, Ristovski, Jayaratne, Keogh, & Ling, 2008). Additionally, other studies showed that the concentration level first increased, and then decreased with increasing height (Huang, Sun, Liu, & Zhang, 2009; Villa, Jayaratne, Gonzalez, & Morawska, 2017). In particular, Jung et al. (2011) found that the highest air pollutant concentration occurred at the 3rd 5th floor levels in New York City. Kalaiarasan et al. (2009) identified that the concentration of PM2.5 was highest at mid-floor (around the 10th floor) of high-rise buildings when compared to values measured at the lower and upper floors in Singapore. One possible reason was that the interception of air pollutants by tree leaves reduced the concentration level at the lower floors (Beckett, Freer Smith, & Taylor, 2000), and the mixture of traffic-polluted air and ambient air at upper floors dilute the particle mass concentration. As for traffic noise, many studies in China found that the intensity of noise increased up to certain heights, then decreased with increasing height, which could presumably be due to the absorption and reflection of roadside trees and road surface. For example, Fan and Lin (2013) found that the noise level reached its maximum at around the 11th15th floor and dropped to its minimum at the 17th21st floor. Through field measurement, theoretical computation and application of noise prediction software, Li et al. (2012) reported that the maximum level of noise was at the eighth floor. Similarity, studies conducted by Li (2011) and Yuan, Lin, and Ping. (2004) showed that the noise was at its maximum level when the height was around the ninth floor.

Second, which variable can be utilized as a good proxy for traffic- related noise and air pollution remains an issue need to be addressed. Given the extreme complexity of the sound and air pollutant propagation, measuring the actual levels of noise and air pollution at the parcel level is difficult and costly. Previous studies often used distance as a proxy for noise intensity (Andersson et al., 2010; Clark, 2006; Seo, Golub, & Kuby, 2014) and air pollution level (Bae, Sandlin, Bassok, & Kim, 2007; Roorda-Knape et al., 1998). However, this method always reflected the combined effect of amenity (accessibility) and disamenity (noise, air pollution) of road traffic, but failed in separating the disamenity effect of traffic-related noise and air pollution from the accessibility. According to Hogan (1973), the level of traffic noise was proportional to the vehicle speed, and the case study conducted in California suggested that controlling the expressway vehicle speed was an effective strategy to reduce noise. Recently, some scholars applied traffic noise prediction models to estimate the level of noise. The main inputs of these models included traffic flow and speed of vehicles (Debnath & Singh, 2018; Golmohammadi, Abbaspour, Nassiri, & Mahjub, 2009; Gulliver et al., 2015; Tansatcha, Pamanikabud, Brown, & Affum, 2005). For instance, Rodríguez-Molares, Sobreira-Seoane, and Martín-Herrero (2011) set a simulation model incorporating traffic speed, traffic flow and traffic composition to estimate the traffic noise, and the results showed that traffic speed was one key factor influencing the noise intensity. Iannone, Guarnaccia, and Quartieri (2013) also found that the noise level was strongly dependent on the vehicle speed. As for air pollution, vehicle emissions contain numerous air pollutants and constitute a main source of air pollution in urban areas (Palmgren, Wahlin, Kildeso, Afshari, & Fogh, 2003; Wehner, Birmili, Gnauk, & Wiedensohler, 2002; Weingartner, Keller, Stahel, Burtscher, & Baltensperger, 1997). Roorda-Knape et al. (1998) found the traffic intensity was an important variable when considering the level of air pollution. Lin, Munsie, Hwang, Fitzgerald, and Cayo (2002) investigated the impact of traffic density on health in Erie County, New York. The results indicated that high traffic density lead to serious air pollution, thereby increasing the incidence of asthma. Through measuring the air pollutant concentration near a major highway, Zhu et al. (2002) found that the changing trend of the air pollutant concentration coincided well with that of traffic density, suggesting that traffic is the major contributor to air pollution. Several studies empirically applied traffic density to measure the disamenity effect of traffic on property value (Hughes & Sirmans, 1992; Kawamura & Mahajan, 2005; Li & Saphores, 2012). For example, Li and Saphores (2012) found that the price of a property was discounted by 0.0057% for every 1% increase in average daily traffic. Therefore, vehicle speed and vehicle density can be considered as good proxies for negative traffic externalities.

Third, the HP model is evidently well suited to estimate the (dis) amenity effect but could be optimized in certain aspects. The traditional hedonic method assumes that property prices are spatially independent from one another, which may be incorrect in the real world. The ignorance of spatial dependence may result in biased and inconsistent estimates (Anselin, 1988; Pace, 1998). Wen et al. (2018b) found that neglecting the spatial effect of housing prices would cause an overestimation in the capitalization effects of education services and other characteristics. By contrast, the spatial econometric model can accurately reflect the spatial dependence in the housing market and obtain robust and reliable results (Hui et al., 2007; Wilhelmsson, 2002). To date, only a few scholars have performed spatial analyses to investigate the effect of traffic externality on property price (Kawamura & Mahajan, 2005; Cellmer, 2011; Seo et al., 2014; Seo, Salon, Kuby, & Golub, 2018). According to the principle for spatial modeling, the existence of spatial dependence must be tested before constructing models (Champ, Bolye, & Brown, 2003). In the current study, the test result shows that Moran's I value is 0.632 and significantly below the 1% level, which confirms the presence of spatial dependence in our dataset. Therefore, this study applied spatial econometric models to optimize the traditional HP model and improve the robustness of results.

3. Data and model

3.1. Study area and data

The study area is Hangzhou City, located in the southeast coast of China. As the capital city of Zhejiang Province, it boasts an advanced economy and a superior geographical position. A survey on the transportation mode of Hangzhou citizens conducted by Jiang (2013) showed the following percentages: 43.33% by motor vehicles, 37.93% by public transit, 12.73% by bicycle, and 6.01% by other methods, which illustrate that transportation by motor vehicle has become the most important. By the end of 2017, the number of motor vehicles in Hangzhou reached 2,793,600, including 1,998,500 private cars, and the per capita car ownership ranked first in China. Hong, Jiao, Xu, Shen, and Ye (2014) found that vehicle emissions constitute the main source of air pollutants

Table 1
Variable definition, quantization, and expected sign.

Class	Variable	Definition	Expected sign
Dependent variable	Property price	Transaction price of a property (CNY)	
Traffic variables	Vehicle speed	Annual average vehicle speed of roads around the community where the property located (km/h)	–
	Vehicle density	Annual average vehicle density of roads around the community where the property located (vehicles/km[1])	–
Structure variables	Floor	Floor where the property is located	? ?
	Size	Property size (m^2)	
	Decoration	Decoration status (4 ¼ best; 1 ¼ worst)	þ
	Age	Age of property (years)	– þ
	Community area	Total area of the community where the property is located (km^2)	
Location variables	Distance to CBD	Distance from the centroid of the community where the property located to the CBD (km)	–
	Distance to West Lake	Distance from the centroid of the community where the property located to closest bank of West Lake (km)	–
	Distance to Qiantang River	Distance from the centroid of the community where the property located to the closest bank of Qiantang River (km)	–
	Population density	Street-level population density where the property is located (people/km^2)	
	Employment density	Street-level employment density where the property is located (/km^2)	– þ
Neighborhood variables	Commuting cost	Average commuting costs of residents in community where the property located (CNY/day)	–
	Subway proximity	Whether the community where the property located is within 1000 m of the closest subway station (1 ¼ yes, 0 ¼ no)	þ
	Bus routes	Number of bus route within 1000 m of the community where the property located	þ
	Bike rental spots	Number of bike rental spot within 100 m of the community where the property located	þ
	Distance to park	Distance from the centroid of the community where the property located to the closest park	–
	Lake proximity	Whether the community where the property located is within 1000 m of the closest lake (except the West Lake) (1 ¼ yes, 0 ¼ no)	–
	Education facility	The quantity and quality of education facilities (4 ¼ best; 1 ¼ worst)	þ
	Living facility	The quantity and quality of living facilities (5 ¼ best; 1 ¼ worst)	þ
	Sports facility	The quantity and quality of sports facilities (5 ¼ best; 1 ¼ worst)	þ
	Property management	The quality of property management (5 ¼ best; 1 ¼ worst)	þ

Note: þ, -, and ? represent positive, negative, and uncertain effects on property price, respectively.

in Hangzhou, contributing 39.5% to $PM_{2.5}$ and resulting in the hazy weather. The 2017 Hangzhou Environment Bulletin also reported that traffic-related noise was the main source of noise pollution. Hangzhou is a prototypical example of cities faced with serious transport issues, especially the negative externalities of vehicular traffic.

This study investigates six main urban districts of Hangzhou, including the Shangcheng, Xiacheng, Gongshu, Jianggan, Xihu, and Binjiang Districts. Owning to the accelerating process of urbanization, the urbanization rate of Hangzhou dramatically increased from 36.52% (2000) to 76.80% (2017). In order to accommodate the increasing population, the supply of high-rise residential buildings has been increasing. Apparently, a scenic view is one popular attraction of high- rise living, but concerns about the high population density in high-rise buildings have also been raised (Wong, 2004; Wong et al., 2011). A number of studies have shown that residents living in areas with high population densities may be subject to various negative effects, such as feelings of overcrowded and stressed (Tanak et al., 1996), reduction of the sense of privacy and tranquility, and rapid spread of communicable diseases (WHO, 2003). Moreover, designs of buildings in different height are usually different, and construction costs also vary with heights (Stone, 1976). Obviously, the price effect for a property on a particular floor of a multi-story building is unequal to the price effect of a dwelling on the same floor of a high-rise building (Wong et al., 2011). In China, residential buildings are divided into multi-story buildings and high-rise buildings according to the residential building code. The division criterion[2] is whether the total floor number of the building exceeds 10. Due to the differences existing between multi-storey and high-rise buildings, the disamenity effect of road traffic on property prices may vary with building heights. Therefore, this study utilizes multi-story and high-rise residential properties as research objects. The real estate market of Hangzhou's main urban area is active and has considerable transaction records, thereby providing sufficient data to investigate the effect of road traffic on property price. The dependent variable is the transaction prices of properties in 2017 obtained from the Hangzhou Real Estate Administration.

3.2. Variable selection

As a typical heterogeneous commodity, property price is determined by a vast array of housing characteristics, such as structure, location, and neighborhood characteristics. This study focuses on the external effect of vehicular traffic on the housing market. Accordingly, we utilize the vehicle speed and vehicle density data provided by the Hangzhou Transportation Bureau as proxies for road-traffic externality. The dataset contains information on the annual average vehicle speed and vehicle density of 217 roads in main urban area of Hangzhou in 2017. We apply TransCAD software to calculate the average vehicle speed and vehicle density of roads around communities where the properties located. To ensure the comprehensiveness and reliability of the dataset, six structural variables, three location variables, and twelve neighborhood variables are chosen as control variables. Table 1 presents the variable measurements and expected effects on property price. The structure variables are included in the dataset obtained from the Hangzhou Real Estate Administration, such as floor, size, decoration, building

[1] GB 50368-2005, Residential building code [S]. Beijing: China Building Industry Press, 2005.

age, and total area of the community. Other characteristics in this dataset, such as total floor, number of bedrooms, and property orientation are not incorporated because of multicollinearity and missing information.

Since the residential community is the basic unit of urban living areas in China, the properties in the same community are likely to exhibit similar interior and exterior public services. In previous empirical studies, data at the community level and spatial regression techniques have been widely used by scholars in China (Liang, Liu, Qiu, Jing, & Fang, 2018; Sun, Zheng, & Wang, 2015; Wang, Feng, Deng, & Cheng, 2016; Wen, Bu, & Qin, 2014). Therefore, the location and neighborhood attributes of properties are collected at the community level in this study. For location variables, the straight-line distance of each community from the Central Business District (CBD), West Lake, and Qiantang River are calculated by GIS software. The distance to CBD indicates the accessibility of the property to the city center, thus reflecting the level of commercial and public services in a property's location. West Lake is the urban landscape center of Hangzhou, which can cause considerable price premiums on the surrounding properties. Qianjiang New City is the new CBD, located in the bank of Qiantang River. Therefore, the distance to Qiantang River is also an important location variable of residential property.

Neighborhood variables are gathered using various methods. Living facility, education facility, sports facility, property management, bus routes, and commuting costs are obtained from a field survey. Among them, living, education, and sports facilities are measured through the content sum. For example, education facility refers to the presence of kindergartens, primary schools, junior high schools, and high schools within 1000 m from the property. Each item scored with 1, and the total score is 4. This quantifying method reduces the number of variables and avoids serious collinearity problems. Commuting cost is obtained by using questionnaires to ask residents' daily commuting costs in each community. In order to control the effect of landscape, variables of distance to parks and lake proximity are incorporated, which are measured from the electronic map. Subway proximity and bike rental spots are also obtained in the same way. Tract-level population and employment densities, which illustrate the socioeconomic level of a property's location, are provided by the Hangzhou Statistics Bureau.

After removing samples with missing information and extreme values, a total of 12,570 valid samples were obtained, including 7590 multi-story property samples and 4980 high-rise property samples. Table 2 shows the descriptive statistics of variables.

3.3. Model specification

(1) Traditional hedonic price model

This study initially constructs the hedonic price models to estimate the disamenity effect of road traffic on property price. Based on the sample data, we applied Box-Cox transformation to probe the best function form (Box & Cox, 1964). Since the vehicle speed and vehicle density are the key variablesand property price is the dependent variable, Box-Cox transformation is implemented into these three variables. According to Chau et al. (2007) and Wen, Bu, and Zhang (2013), we tested four special forms of linear, semi-logarithmic, logarithmic and inverse semi-logarithmic, and then carried out the loglikelihood ratio (LR) test to select the best model. Results shows that the maximum log-likelihood value of 184804.33 was obtained from the logarithmic model. Critical values of the chi-square distribution with two degrees of freedom at the 1% and 5% significant levels were 9.210 and 5.991, respectively. The LR statistic values of linear, semi-logarithmic and inverse semi-logarithmic models were 9270.28, 185.04 and 9180.24, respectively, far greater than 9.210. Accordingly, these three models were rejected at the 1% level, and the logarithmic model was the optimal model for further estimation. Specifically, the dependent variable and continuous independent variables are adopted into the logarithmic form, whereas dummy variables and other discrete variables are adopted into the linear form. Thus, the basic model is defined as follows:

$$\mathrm{Ln}P = \alpha_0 + \sum \alpha_i \mathrm{Ln}T_i + \sum \beta_j \mathrm{Ln}X_j + \sum \gamma_k Z_k + \varepsilon \quad (1)$$

where P is the property price; T_i are the road traffic externality variables; X_j represents other continuous variables; Z_k refers to discrete variables; α_0, α_i, β_j, and γ_k are the coefficients to be estimated, and ε is an error term.

Owing to the vertical distribution variation of the traffic-related noise and air pollution, their capitalization effects on property prices may vary significantly at different floors. To explore the moderating effect of floor level on road-traffic external effects, models incorporating interaction in terms of floor level and road traffic characteristics are estimated. The interactive model is as follows:

Table 2
Statistical description.

Variables	Minimum	Maximum	Mean	Standard deviation
Property price	700,000	11,500,000	2,946,869.150	1,607,391.811
Vehicle speed	20.300	63.953	29.282	6.375
Vehicle density	328.270	6791.058	2493.931	2128.718
Floor	1	33	6.32	5.227
Size	50.000	200.000	98.728	36.066
Decoration	1	4	2.540	0.673
Age	4	38	17.660	6.602
Community area	0.003	0.333	0.061	0.055
Distance to CBD	0.420	12.790	5.291	2.829
Distance to West Lake	0.530	13.100	4.675	2.288
Distance to Qiantang River	0.100	16.532	6.973	4.060
Population density	951.369	92,846.512	24,506.760	15,910.589
Employment density	86.472	52,602.030	8817.369	8121.638
Commuting cost	0.429	13.308	2.403	0.985
Subway proximity	0	1	0.100	0.297
Bus routes	0	34	9.850	7.187
Bike rental spots	0	20	3.070	2.915
Distance to park	0.060	4.150	1.008	0.699
Lake proximity	0	1	0.300	0.183
Education facility	1	4	3.010	0.818
Living facility	0	5	4.090	1.293
Sports facility	0	5	2.320	1.356
Property management	1	5	2.810	1.262

$$\mathrm{Ln}P = \alpha_0 + \sum \alpha_i \mathrm{Ln}T_i + \sum \beta_j \mathrm{Ln}X_j + \sum \gamma_k Z_k + \mu \mathrm{Ln}F + \sum \delta_m (\mathrm{Ln}T_i \times \mathrm{Ln}F) + \varepsilon \quad (2)$$

where F is the floor where the property is situated; μ, δ_m are the coefficients to be estimated; and the remaining variables are the same as Equation (1).

The models mentioned above assume that the housing market of the entire city is unified and that the housing price can be explained by a single hedonic price equation. In reality, an urban housing market can be segmented into a series of submarkets according to supply- or demand-related factors, such as location, neighborhood, and structural characteristics; moreover, the implicit price of a housing characteristic may vary across different submarkets (Anas & Eum, 2006; Goodman, 1981; Straszheim, 1975). Goodman and Thibodeau (2003) and Tu (1997) have proven that submarket structure was relevant when analyzing urban housing markets and helped obtain accurate estimates. Therefore, market segmentation is necessary when investigating how road-traffic externalities function in separate submarkets. Based on the structure of our sample data and study backgrounds, the whole market is divided into multi-story (Submarket M) and high-rise (Submarket H) submarkets according to the total floor number of the building. Equation (1) defines the model expression in submarkets. In addition, interactive terms are included to investigate the moderating effect in submarkets, and Equation (2) defines the model expression.

To confirm the hypothesis that the disamenity effect of road traffic may vary across different floor levels, this study further subdivides Submarkets M and H based on data structure and prediction accuracy of subsamples. Submarket M is divided into three submarkets located on low-, middle-, and high-floors of multi-story buildings. The first submarket (Submarket ML) consists of properties from the 1st to 3rd floor. The second submarket (Submarket MM) consists of properties from the 4th to 6th floor. The last submarket (Submarket MH) consists of properties from the 7th to 9th floor. Similarly, Submarket H is divided into four submarkets located on low-, medium-low-, medium-high-, and high-floors of high-rise buildings. The first submarket (Submarket HL) consists of properties from the 1st to 5th floor. The second submarket (Submarket HML) consists of properties from the 6th to 10th floor. The third submarket (Submarket HMH) consists of properties from the 11th to 20th floor. The last submarket (Submarket HH) consists of properties above the 20th floor. Their model expressions are followed by Equation (1).

As Goodman and Thibodeau (2003) suggested, it is necessary to test whether the submarket constructions have preferable prediction accuracy or not. In order to examine the prediction accuracy for the submarket constructions of this study, the whole sample is randomly separated into two subsamples: a prediction subsample (1257 transactions) and an estimation subsample (11,313 transactions). The frequency distributions of the proportional error (PPE) for submarket models are reported in table A1 in the Appendix. The empirical results indicate that submarket segmentations yield significant improvements in hedonic prediction accuracy. For example, from the cumulative distribution of PPEs, approximately 80% of the submarket models predicted prices within 20% of observed transaction prices, while that of the whole market model is only 69%.

(2) Spatial econometric model

Traditional hedonic price model neglects the spatial dependence of property prices, resulting in unbiased results. This study applies SLM and SEM to improve the above hedonic price models. Equations (3) and (6) provide the formula form of SLM. Equation (4) – (5) and (7)–(8) provide the form of SEM.

$$\mathrm{Ln}P = \alpha_0 + \rho W \mathrm{Ln}P + \sum \alpha_i \mathrm{Ln}T_i + \sum \beta_j \mathrm{Ln}X_j + \sum \gamma_k Z_k + \varepsilon \quad (3)$$

$$\mathrm{Ln}P = \alpha_0 + \sum \alpha_i \mathrm{Ln}T_i + \sum \beta_j \mathrm{Ln}X_j + \sum \gamma_k Z_k + \varepsilon \quad (4)$$

$$\varepsilon = \lambda W \varepsilon + \mu \quad (5)$$

$$\mathrm{Ln}P = \alpha_0 + \rho W \mathrm{Ln}P + \sum \alpha_i \mathrm{Ln}T_i + \sum \beta_j \mathrm{Ln}X_j + \sum \gamma_k Z_k + \mu \mathrm{Ln}F + \sum \delta_m (\mathrm{Ln}T_i \times \mathrm{Ln}F) + \varepsilon \quad (6)$$

$$\mathrm{Ln}P = \alpha_0 + \sum \alpha_i \mathrm{Ln}T_i + \sum \beta_j \mathrm{Ln}X_j + \sum \gamma_k Z_k + \mu \mathrm{Ln}F + \sum \delta_m (\mathrm{Ln}T_i \times \mathrm{Ln}F) + \varepsilon \quad (7)$$

$$\varepsilon = \lambda W \varepsilon + \mu \quad (8)$$

where W is the spatial weight matrix, ρ is the spatial autocorrelation coefficient, $W\mathrm{Ln}P$ is the spatial lag term, $W\varepsilon$ is the spatial error term, λ is the coefficient to be estimated, and the remaining variables are the same as the basic model.

4. Results and discussion

4.1. Overall effect of road-traffic externalities

Table 3 exhibits the estimated results for the whole sample. All models are statistically significant at 1% level, which confirms the validity of these models. The adjusted R^2 values of the three models are 0.842, 0.855, and 0.870, respectively, indicating that these models provide good fits with more than 80% variance of the dependent variable explained. Among the variance inflation factor (VIF) values of independent variables, the minimum value is 1.147 and the maximum value is 6.870, both smaller than 10. This result demonstrates that the level of multicollinearity can be considered not serious. Meanwhile, the statistical test result of the three models shows that SEM has the largest LogL value and the smallest AIC and SC values. These findings indicate that SEM has the best explaining ability among the three models. Therefore, this study applies the results of the SEM for subsequent analyses.

In the SEM, regression coefficients of vehicle speed and vehicle density are 0.221 and 0.100, respectively, and significance levels are both below 1%, indicating that the road-traffic externalities are negative in relation to property prices. Specifically, when the vehicle speed and vehicle density around a property increased by 1%, the property price will decrease by 0.221% and 0.100%, respectively. An increase in the speed or density of motor vehicles will increase the noise intensity and air pollution, thus resulting in a negative capitalization effect on property prices. In addition, the absolute value of the coefficient of vehicle speed is larger than that of vehicle density, which indicates that the disamenity effect of vehicle speed on property price is greater than that of vehicle density.

To reflect the transportation facilities surrounding a property and avoid variable omission problem, this study selects a number of traffic- related characteristic variables as control variables, including bus routes, subway proximity, bike rental spots, and commuting costs. The regression coefficients of these control variables are significant at the 1% level. However, the signs of coefficients of bus routes and bike rental spots are negative, which contradicts expectation. One possible reason is that too many bus routes surrounding a property usually mean serious environmental issues, including worsened air quality, noise disturbance, and traffic congestion. Consequently, such problems negatively influence property price. This phenomenon is also found in previous empirical studies in Hangzhou (Wen, Gui, Tian, Xiao, & Fang, 2018a; Xiao et al., 2019). As for bike variable, a property in close proximity to many bike rental spots is generally located in an area with inadequate transportation facilities. Consequently, the bike rental spots variable also yields a negative influence on property price.

Overall, most regression coefficients of control variables are statistically significant at less than the 10% level. As expected, all the location variables (Distance to West Lake, Distance to CBD, and Distance to Qiantang River) are significant and negatively influence property price, which are in line with the conclusion of previous studies on the Hangzhou real estate market (Wen et al., 2017a; 2017b; 2018a). Similarly, most structural variables and neighborhood variables also correlate with expected signs. For example, age is equal to the transaction year minus actual built year, which has a negative relationship with property value. Socioeconomic variables, such as population and job densities, significantly affect property price with expected signs. Population density negatively influences property price, whereas job density has a positive influence on the latter.

4.2. Moderating effect of floor level on traffic externalities

To explore the vertical spatial heterogeneity of the disamenity effect of road traffic, the interactive entries of floor level and traffic externalities are added into the basic model. As shown in Table 4, the regression coefficients of interactive items pass the 10% significance test, and values are 0.049 and 0.005, respectively, revealing that floor level has a positive moderating effect on the disamenity effect of road traffic on property price. Generally, the negative price effects of traffic externalities experience an upward trend with the increasing floor level. By contrast, the basic model can only catch the average implicit price of road traffic characteristics, which underestimates the effects on properties situated in the upper floors and overestimates those in the lower floor levels.

Table 5 shows the results of Submarkets M and H. The regression coefficients of vehicle speed and vehicle density are significant at 1% level with negative signs, indicating that road-traffic externalities are negative in relation to property prices in these two submarkets. In particular, in Submarket M, the price elasticity coefficients of vehicle speed and vehicle density are 0.174 and 0.117, respectively. Taking a standard property (the property with values of all characteristics equal

Table 3

Regression results of overall market.

Variable	OLS			SLM		SEM	
	Coef.	*p*-value	VIF	Coef.	*p*-value	Coef.	*p*-value
Constant	13.200***	<0.0005		10.683***	<0.0005	13.022***	<0.0005
Ln (Vehicle speed)	0.236***	<0.0005	1.984	0.214***	<0.0005	0.221***	<0.0005
Ln (Vehicle density)	0.109***	<0.0005	1.931	0.094***	<0.0005	0.100***	<0.0005
Ln (Floor)	0.007*	0.077	1.726	0.006*	0.062	0.008*	0.071
Ln (Size)	0.973***	<0.0005	1.749	0.893***	<0.0005	0.959***	<0.0005
Decoration	0.001	0.703	1.021	0.001	0.615	0.000	0.895
Ln (Age)	0.279***	<0.0005	3.451	0.227***	<0.0005	0.263***	<0.0005
Ln (Community area)	0.018***	<0.0005	2.050	0.017***	<0.0005	0.019***	<0.0005
Ln (Distance to CBD)	0.077***	<0.0005	4.870	0.070***	<0.0005	0.053***	<0.0005
Ln (Distance to West Lake)	0.232***	<0.0005	3.645	0.204***	<0.0005	0.246***	<0.0005
Ln (Distance to Qiantang River)	0.022***	<0.0005	3.377	0.020***	<0.0005	0.015***	<0.0005
Ln (Population density)	0.040***	<0.0005	2.153	0.034***	<0.0005	0.038***	<0.0005
Ln (Employment density)	0.022***	<0.0005	1.388	0.019***	<0.0005	0.019***	<0.0005
Ln (Commuting cost)	0.037***	<0.0005	1.323	0.031***	<0.0005	0.033***	<0.0005
Subway proximity	0.063***	<0.0005	1.330	0.057***	<0.0005	0.060***	<0.0005
Ln (Bus routes)	0.010***	<0.0005	1.429	0.007***	<0.0005	0.009***	<0.0005
Ln (Bike rental spots)	0.020***	<0.0005	1.785	0.016***	<0.0005	0.019***	<0.0005
Ln (Distance to park)	0.067***	<0.0005	1.589	0.057***	<0.0005	0.064***	<0.0005
Lake proximity	0.016	0.141	1.147	0.011	0.310	0.032**	0.011
Education facility	0.063***	<0.0005	1.444	0.053***	<0.0005	0.061***	<0.0005
Living facility	0.004	0.120	2.808	0.004*	0.064	0.006**	0.020
Sports facility	0.026***	<0.0005	2.500	0.022***	<0.0005	0.026***	<0.0005
Property management	0.029***	<0.0005	2.816	0.022***	<0.0005	0.032***	<0.0005
ρ				0.171***	<0.0005		
λ						0.343***	<0.0005
Adjusted R^2	0.841			0.855		0.870	
LogL	1907			2385		2748	
AIC	3766.55			4720.42		5448.07	
SC	3587.87			4534.30		5269.40	

Note: ***, **, and * represent the statistical significance at 1%, 5%, and 10% level, respectively. The number of the whole sample is 12,570, and the value of Moran's I is 0.632.

Table 4

Regression results of interactive model.

Variable	OLS		SLM		SEM	
Constant	12.813***	<0.0005	10.346***	<0.0005	12.634***	<0.0005
Ln (Vehicle speed)	0.155***	<0.0005	0.158***	<0.0005	0.129***	0.001
Ln (Vehicle density)	0.096***	<0.0005	0.077***	<0.0005	0.092***	<0.0005
Ln (Vehicle speed) * Ln (Floor)	0.044***	0.006	0.030**	0.045	0.049***	0.006
Ln (Vehicle density) * Ln (Floor)	0.008**	0.078	0.010**	0.018	0.005**	0.056
Ln (Floor)	0.214***	0.001	0.186***	0.003	0.211***	0.003
Ln (Size)	0.973***	<0.0005	0.893***	<0.0005	0.959***	<0.0005
Decoration	0.001	0.739	0.001	0.637	<0.005	0.861
Ln (Age)	0.276***	<0.0005	0.224***	<0.0005	0.259***	<0.0005
Ln (Community area)	0.017***	<0.0005	0.016***	<0.0005	0.018***	<0.0005
Ln (Distance to CBD)	0.078***	<0.0005	0.072***	<0.0005	0.054***	<0.0005
Ln (Distance to West Lake)	0.231***	<0.0005	0.203***	<0.0005	0.245***	<0.0005
Ln (Distance to Qiantang River)	0.022***	<0.0005	0.020***	<0.0005	0.015***	<0.0005
Ln (Population density)	0.040***	<0.0005	0.034***	<0.0005	0.038***	<0.0005
Ln (Employment density)	0.021***	<0.0005	0.019***	<0.0005	0.019***	<0.0005
Ln (Commuting costs)	0.037***	<0.0005	0.031***	<0.0005	0.033***	<0.0005
Subway proximity	0.063***	<0.0005	0.057***	<0.0005	0.060***	<0.0005
Ln (Bus routes)	0.010***	<0.0005	0.007***	0.004	0.009***	0.002
Ln (Bike rental spots)	0.019***	<0.0005	0.015***	<0.0005	0.018***	<0.0005
Ln (Distance to park)	0.066***	<0.0005	0.056***	<0.0005	0.063***	<0.0005
Lake proximity	0.016	0.143	0.011	0.310	0.032**	0.012
Education facility	0.063***	<0.0005	0.053***	<0.0005	0.062***	<0.0005
Living facility	0.004	0.113	0.004*	0.064	0.006**	0.023
Sports facility	0.026***	<0.0005	0.023***	<0.0005	0.026***	<0.0005
Property management	0.030***	<0.0005	0.023***	<0.0005	0.033***	<0.0005
ρ			0.171***	<0.0005		
λ					0.343***	<0.0005
Adjusted R^2	0.842		0.856		0.870	
LogL	1918		2396		2760	
AIC	3784.13		4738.6		5468.96	
SC	3590.57		4537.6		5275.4	

Note: ***, **, and * represent the statistical significance at 1%, 5%, and 10% level, respectively. The number of the whole sample is 12,570, and the value of Moran's I is 0.632.

to the mean market value) as an example, price decreases by 4071.826 Yuan and 2373.952 Yuan when the vehicle speed and density increases by 1%, respectively. In Submarket H, the price elasticity coefficients of vehicle speed and vehicle density are respectively 0.254 and 0.094, indicating that every 1% increase in vehicle speed brings about a 9818.345 Yuan decrease in property price, and every 1% increase in vehicle density brings about a 3633.561 Yuan decrease. These results also indicate that the disamenity effect of road traffic on high-rise buildings is greater than that on multi-story buildings.

Columns (2) and (4) of Table 5 present the results of interactive models. The signs and significance levels of vehicle speed and vehicle density remain relatively steady, whereas most interactive terms are insignificant, except for the interactive term of floor level and vehicle density in Submarket M. Thus, the moderating effect of floor level is implied to exist only on the capitalization effect of vehicle density on property value in Submarket M. The possible reason is that a nonlinear relationship exists between road-traffic externalities and floor level. Therefore, further dividing Submarkets M and H by floor where the property is located is necessary to acquire an accurate effect of road traffic on property price.

4.3. Vertical dimension analysis of traffic external effects

Table 6 lists the regression results of multi-story submarkets (Submarket ML, MM, and MH). The vertical patterns of the relationships between road traffic externalities and property price are represented in Fig. 1. Specifically, the coefficients of vehicle speed of the three submarkets are 0.185, 0.188, and 0.264, respectively, and are significant at 1% level. Thus, the disamenity effect of vehicle speed is indicated to undergo a climbing tendency from Submarkets ML to MH. Similarly, the coefficients of vehicle density are separately 0.104,

0.123, and 0.148, suggesting that the negative effect of vehicle density on property price also increases with the rising floor level. These findings may be related to the vertical distribution profiles of noise and air pollution levels generated by motor vehicles. Since Hangzhou has large green space areas with its urban green coverage rate reaching to around 40% in 2017, the interception and absorption of noise wave and air pollutants by roadside trees may lower their levels at the lower floors. So, the levels of noise and air pollution first increase up to certain heights, then decrease with increasing height. Based on previous studies, the maximum levels may appear at around the 10th floor (Fan & Lin, 2013; Kalaiarasan et al., 2009; Li, 2011; Li et al., 2012). In terms of multi-story buildings ranging from two to nine floors, the levels of traffic-related noise and air pollution both experience upward movements with the increasing floor levels. Therefore, the negative influence of vehicle speed and vehicle density on property prices increase as floor level rises.

Table 7 exhibits the results of high-rise submarkets (Submarket HL, HML, HMH, and HH). The vertical patterns of the relationships between road traffic externalities and property price in Submarket H are represented in Fig. 2. Specifically, the regression coefficients of vehicle speed in the four submarkets are 0.262, 0.272, 0.272, and 0.271 respectively, and pass the 1% significance level test. Thus, the negative capitalization effect of vehicle speed on property price first increases with the rising floor level and then declines slowly, which is probably due to the vertical distribution of traffic-related noise. The highest value of noise intensity may appear in Submarket HML or Submarket HMH, resulting the same price elastic coefficient of vehicle speed in these two submarkets. In Submarket HH, the disamenity effect on property price still remains at a relatively high level, which implies these homebuyers valuing quiet environment as an important factor during the decision- making process. As for vehicle density, the regression coefficients in the four submarkets are 0.088, 0.048, 0.118, and 0.107, respectively, indicating that every 1% increase in vehicle density brings about 0.088%, 0.048%, 0.118%, and 0.107% decrease in property price from Submarket HL to HH. Notably, the magnitude of negative external effects exhibits a nonlinear variation in the vertical dimension: the maximum effect appears in Submarket HMH, whereas the minimum effect is in Submarket HML. According to previous empirical studies, the concentration of air pollutants may reach to the maximum value in Submarket HMH, which can explain why the greatest negative effect of vehicle density occurs in this submarket. In addition, the negative effect in Submarket HH also remains at a relatively high level. One possible reason is that homebuyers of properties on upper floors pursue good environment when making purchase decision, which results in less tolerance for traffic-related pollution than that of homebuyers in lower submarkets.

5. Conclusions

This study employs traditional hedonic price model and spatial econometric model to quantify the microscopic effect of road-traffic externalities on property price. Compared with existing studies, this study specifically focuses on the moderating effect of floor level and the vertical heterogeneity of road traffic external effect on property price. A better understanding of the relationship between road-traffic externalities and property value is provided, and the main conclusions are as follows:

(1) Road traffic externalities (e.g., noise and air pollution) significantly decrease property price, and the negative effect generated by vehicle speed is larger than that generated by vehicle density. In general, every 1% increase in the vehicle speed and vehicle density surrounding a property separately results in an average decrease of 0.221% and 0.100% in property price. This finding reveals that as people put extra emphasis on physical health and quality of living environment, homebuyers are willing to pay price premiums for reduced exposure to negative traffic externalities.
(2) The floor level evidently has a significant moderating effect on the disamenity effect of road traffic. Overall, the negative capitalization rates of road traffic display an upward trend with the increasing floor level, which illustrates that properties located on upper floor levels are more affected by road-traffic externalities than those on medium and lower floor levels. However, previous studies are mostly based on the simple assumption that all properties share the same effects of road-traffic externalities in a housing market. This notion underestimates the effects on properties situated in the upper floors and overestimates those in the lower floor levels. In actuality, the moderating effect between floor level and road-traffic externalities is complicated and exhibits different behaviors in multi-story and high-rise buildings.
(3) From the submarket level, the findings further reveal the vertical spatial heterogeneity of disamenity effect of road traffic, implying that traffic externalities affect property prices differently even within the same building. For multi-story buildings, the disamenity effects generated by vehicle speed and vehicle density both demonstrate a climbing trend as floor level rises. For high- rise buildings, the results are remarkably different. The negative effect of vehicle speed first increases with the rising floor level and then decreases slowly. In terms of the disamenity effect of vehicle density, the utmost effect on property price appears in Submarket HMH, whereas the smallest effect occurs in Submarket HML.

In summary, the relationship between road-traffic externalities and property value is complicated in vertical spatial dimension and behaves differently in each submarket. Under the context that people living in urban area are increasingly sensitive to negative externalities generated by road traffic, the novel conclusions of this study should be of interest to them. These conclusions should also be of great importance to developers and policy makers at a time when the road traffic demand is

Table 5
Regression results of Submarkets M and H.

Variable	Submarket M (1)			Interactive model- Submarket M (2)			Submarket H (3)			Interactive model- Submarket H (4)		
	OLS	SLM	SEM	OLS	SLM	SEM	OLS	SLM	SEM	OLS	SLM	SEM
Constant	13.536***	10.156***	13.400***	13.227***	9.864***	13.035***	13.020***	11.383***	12.879***	13.010***	11.309***	12.958***
Ln (Vehicle speed)	~~0.201***~~	~~0.180***~~	~~0.174***~~	~~0.173***~~	~~0.154***~~	~~0.129*~~	~~0.272***~~	~~0.261***~~	~~0.254***~~	~~0.316***~~	~~0.287***~~	~~0.307***~~
Ln (Vehicle density)	0.122***	0.103***	0.117***	0.092***	0.075***	0.087***	0.105***	0.096***	0.094***	0.083***	0.074***	0.080***
Ln (Vehicle speed)* Ln (Floor)				0.019	0.018	0.031				0.020	0.012	0.024
Ln (Vehicle density) * Ln (Floor)				0.020**	0.019**	0.020**				0.009	0.010	0.006
Ln (Floor)	0.008	0.011	0.006	0.208*	0.195*	0.249*	0.011**	0.011**	0.011*	0.014	0.042	0.026
Ln (Size)	0.973***	0.877***	0.957***	0.973***	0.877***	0.957***	0.999***	0.965***	0.995***	0.999***	0.965***	0.994***
Decoration	0.016***	0.014***	0.012***	0.016***	0.014***	0.012***	0.015***	0.014***	0.014***	0.015***	0.013***	0.014***
Ln (Age)	0.196***	0.136***	0.175***	0.196***	0.136***	0.174***	0.319***	0.302***	0.314***	0.319***	0.302***	0.315***
Ln (Total area of community)	0.024***	0.022***	0.022***	0.024***	0.022***	0.022***	0.010*	0.008	0.013**	0.010*	0.008	0.013**
Ln (Distance to CBD)	0.078***	0.066***	0.062***	0.078***	0.067***	0.063***	0.024*	0.023*	0.006	0.024*	0.024**	0.006
Ln (Distance to West Lake)	0.207***	0.177***	0.215***	0.207***	0.177***	0.215***	0.318***	0.294***	0.324***	0.317***	0.293***	0.323***
Ln (Distance to Qiantang River)	0.049***	0.040***	0.048***	0.049***	0.041***	0.049***	0.001	0.002	0.007	0.001	0.002	0.007
Ln (Population density)	0.053***	0.031***	0.053***	0.053***	0.031***	0.053***	0.017***	0.016***	0.018***	0.017***	0.016***	0.018***
Ln (Employment density)	0.020***	0.015***	0.013***	0.019***	0.014***	0.013***	0.001	0.001	0.001	0.001	0.000	0.002
Ln (Commuting costs)	0.063***	0.049***	0.054***	0.064***	0.049***	0.054***	0.009	0.007	0.001	0.008	0.006	0.000
Subway proximity	0.072***	0.061***	0.069***	0.072***	0.062***	0.070***	0.053***	0.051***	0.053***	0.053***	0.052***	0.054***
Ln (Bus routes)	0.011***	0.008***	0.009**	0.011***	0.008***	0.009**	0.002	0.002	0.000	0.002	0.002	0.000
Ln (Bike rental spots)	0.038***	0.030***	0.033***	0.038***	0.030***	0.033***	0.000	0.001	0.007	0.000	0.001	0.007
Ln (Distance to park)	0.072***	0.056***	0.069***	0.071***	0.056***	0.069***	0.039***	0.037***	0.039***	0.038***	0.037***	0.038***
Lake proximity	0.040***	0.028**	0.040***	0.040***	0.029**	0.040***	0.024	0.024	0.004	0.024	0.023	0.004
Education facility	0.067***	0.052***	0.063***	0.067***	0.052***	0.063***	0.073***	0.068***	0.073***	0.073***	0.068***	0.073***
Living facility	0.002	0.002	0.005	0.002	0.002	0.005	0.010***	0.008***	0.009***	0.010***	0.008***	0.009***
Sports facility	0.005*	0.002	0.009***	0.005	0.002	0.009***	0.039***	0.037***	0.038***	0.039***	0.037***	0.038***
Property management	0.032***	0.023***	0.035***	0.032***	0.024***	0.035***	0.050***	0.046***	0.049***	0.050***	0.046***	0.049***
ρ		0.214***			0.214***			0.108***			0.108***	
λ			0.407***			0.407***			0.245***			0.244***
Adjusted R^2	0.809	0.833	0.857	0.809	0.834	0.857	0.836	0.844	0.852	0.837	0.845	0.852
LogL	1473	1889	2214	1477	1893	2216	1389	1488	1545	1391	1489	1546
AIC	2899	3728	4379	2902	3731	4381	2730	2925	3042	2730	2924	3041
SC	2733	3555	4213	2722	3544	4201	2574	2762	2886	2560	2748	2871

Note: ***, **, and * represent the statistical significance at 1%, 5%, and 10% level, respectively. The number of Submarkets M and H samples are 7590 and 4,980, respectively. The value of Moran's I of Submarkets M and H samples are 0.656 and 0.448, respectively.

Table 6
Regression results of multi-story submarkets.

Variable	Submarket ML			Submarket MM			Submarket MH		
	OLS	SLM	SEM	OLS	SLM	SEM	OLS	SLM	SEM
Constant	12.974***	9.604***	12.931***	13.979***	10.470***	13.786***	12.937***	11.344***	12.798***
Ln (Vehicle speed)	0.213***	0.192***	0.185***	0.219***	0.193***	0.188***	0.301***	0.270***	0.264***
Ln (Vehicle density)	0.107***	0.090***	0.104***	0.127***	0.108***	0.123***	0.153***	0.140***	0.148***
Ln (Size)	1.008***	0.904***	0.985***	0.955***	0.864***	0.942***	0.922***	0.884***	0.926***
Decoration	0.023***	0.020***	0.016***	0.004	0.005	0.004	0.001	0.000	0.003
Ln (Age)	0.163***	0.108***	0.147 ***	0.216***	0.151***	0.192***	0.231***	0.185***	0.194***
Ln (Total area of community)	0.020***	0.018***	0.019***	0.024***	0.023***	0.024***	0.015	0.018	0.005
Ln (Distance to CBD)	0.085***	0.079***	0.083***	0.067***	0.054***	0.041***	0.120***	0.104***	0.115***
Ln (Distance to West Lake)	0.181***	0.148***	0.173***	0.233***	0.202***	0.254***	0.182***	0.171***	0.183***
Ln (Distance to Qiantang River)	0.055***	0.047***	0.055***	0.044***	0.036***	0.042***	0.093***	0.075***	0.077***
Ln (Population density)	0.042***	0.021***	0.043***	0.057***	0.032***	0.053***	0.040***	0.038**	0.057***
Ln (Employment density)	0.018***	0.011***	0.012**	0.020***	0.017***	0.014***	0.014	0.011	0.014
Ln (Commuting costs)	0.043***	0.031***	0.042***	0.060***	0.046***	0.053***	0.111***	0.106***	0.086***
Subway proximity	0.052***	0.043***	0.049***	0.070***	0.060***	0.066***	0.105***	0.098***	0.115***
Ln (Bus routes)	0.013***	0.010**	0.011**	0.009**	0.007*	0.011**	0.010	0.006	0.006
Ln (Bike rental spots)	0.048***	0.036***	0.040***	0.029***	0.023***	0.028***	0.017	0.016	0.011
Ln (Distance to park)	0.070***	0.053***	0.069***	0.064***	0.051***	0.061***	0.061***	0.060***	0.062***
Lake proximity	0.016	0.005	0.023	0.050***	0.041**	0.040*	0.284***	0.233***	0.240***
Education facility	0.077***	0.060***	0.072***	0.062***	0.048***	0.058***	0.041***	0.035***	0.043***
Living facility	0.002	0.002	0.008	0.003	0.001	0.009	0.012	0.017	0.015
Sports facility	0.007	0.004	0.013***	0.002	0.000	0.005	0.016	0.014	0.020*
Property management	0.034***	0.023***	0.036***	0.028***	0.021***	0.033***	0.026**	0.026***	0.031***
ρ		0.221***			0.214***			0.130***	
λ			0.408***			0.428***			0.313***
Adjusted R^2	0.815	0.84	0.861	0.814	0.838	0.865	0.851	0.865	0.876
LogL	718	935	1077	713	905	1090	227	237	249
AIC	1389	1823	2108	1381	1762	2135	409	427	451
SC	1246	1674	1965	1240	1615	1994	312	326	355
N	3693			3405			492		
Moran's I	0.659			0.668			0.659		

Note: ***, **, and * represent the statistical significance at 1%, 5%, and 10% level, respectively. The number of Submarket ML, MM, and MH samples are 3693; 3405; and 492, respectively. The value of Moran's I of Submarket ML, MM, and MH samples are 0.659, 0.668, and 0.459, respectively.

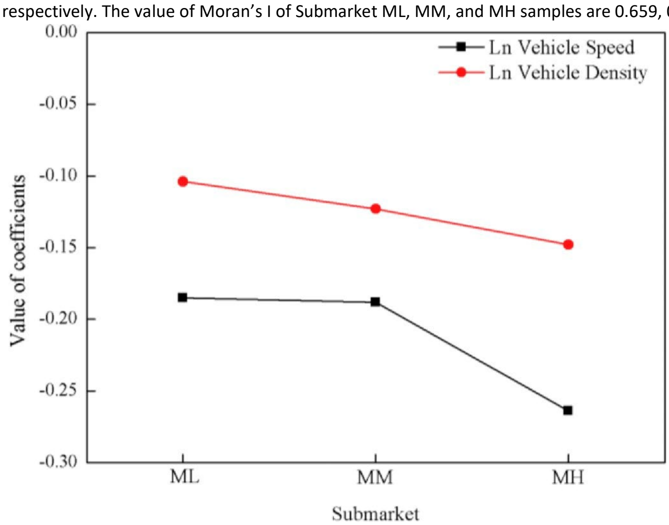

Fig. 1. Vertical pattern of the relationship between road traffic and property price (Submarket M). continuous growing as the economic development.

(1) Residential properties in multi-storey buildings and high-rise buildings are subjected to the disamenity effect of road traffic in Hangzhou, and this effect varies with their floor levels and building heights. Properties located on the 7th 9th floor in multi- storey buildings and on the 11th 20th floor in high-rise buildings suffer from the most serious disamenity effect, which may offer some implications on the decision-making process to homebuyers and pricing strategy to developers. Moreover, the developers may consider to take some measures to effectively insulate these properties from negative externalities caused by road traffic, such as surrounding balconies with glass and installing double-glazed window during construction period.
(2) The government may consider to set sound barriers or building noise-reduction green belts between urban road and residential buildings, which is helpful to alleviate the disamenity effect of road traffic. Sound barriers are known to reflect noise sound waves and intercept the spread of air pollutants, thus effectively relieving the negative effect of road traffic. Similarly, green belts can also reflect noise sound waves, absorb harmful gases, and absorb certain

air pollutants, thereby reducing the level of road traffic-related noise and air pollution. In addition, the efficiency and reliability of public transportation systems are also extremely important as they can encourage people to opt for the mass transit rather than drive private motor vehicles. Furthermore, extra attention should be paid to the research and promotion of vehicles running on renewable energy, which can relieve the negative effect of road traffic from the source.

Finally, there are of course a range of limitations in this study. First, this study only covers one city and, therefore, the results cannot be generalized to other cities. Further studies cover other cities inside and outside of China would contribute to improve the universality of the results. Second, the detailed information about the sound decibel and the air pollutant concentration of each property is not available in this study. Further work could consider to measure the exact levels of noise and air pollution from traffic of each property, which can reveal the disamenity effect of road traffic on property price directly. Third, because of the privacy protection, the precise spatial location of each property inside a community is not provided by the real estate agency. Thus, the location and neighborhood characteristics of each property cannot be measured in this study. Following common practices in the

Table 7
Regression results of high-rise submarkets.

Variable	Submarket HL			Submarket HML			Submarket HMH			Submarket HH		
	OLS	SLM	SEM	OLS	SLM	SEM	OLS	SLM	SEM	OLS	SLM	SEM
Constant	12.842***	10.933***	12.723***	12.700***	11.244***	12.658***	13.311***	12.026***	13.265***	13.115***	13.014***	12.986***
Ln (Vehicle speed)	−0.275***	−0.251***	−0.262***	−0.281***	−0.266***	−0.272***	−0.281***	−0.283***	−0.272***	−0.270***	−0.267***	−0.271***
Ln (Vehicle density)	−0.092***	−0.083***	−0.088***	−0.053***	−0.049***	−0.048***	−0.125***	−0.114***	−0.118***	−0.113***	−0.113***	−0.107***
Ln (Size)	0.967***	0.926***	0.963***	0.986***	0.956***	0.971***	0.979***	0.954***	0.976***	1.025***	1.023***	1.031***
Decoration	0.045***	0.043***	0.042***	−0.010	−0.012	−0.010	0.015**	0.015**	0.016**	0.004	0.004	0.006
Ln (Age)	−0.294***	−0.265***	−0.290***	−0.332***	−0.318***	−0.314***	−0.280***	−0.275***	−0.289***	−0.199***	−0.198***	−0.188***
Ln (Total area of community)	0.002	−0.001	0.000	0.023**	0.019*	0.026**	0.017	0.016	0.019*	0.022	0.021	0.035
Ln (Distance to CBD)	−0.080**	−0.076**	−0.060**	0.025	0.024	0.032	−0.039	−0.041*	−0.028	0.057	0.057	0.059
Ln (Distance to West Lake)	−0.214***	−0.194***	−0.226***	−0.273***	−0.260***	−0.274***	−0.344***	−0.318***	−0.350***	−0.481***	−0.480***	−0.480***
Ln (Distance to Qiantang River)	−0.012	−0.010	−0.005	−0.006	−0.004	−0.002	0.000	−0.003	0.002	0.059***	0.058***	0.060***
Ln (Population density)	−0.023***	−0.021***	−0.022***	−0.031***	−0.029***	−0.034***	−0.001	−0.002	−0.002	−0.044***	−0.044***	−0.043***
Ln (Employment density)	−0.009	−0.008	−0.003	0.028***	0.028***	0.030***	−0.015**	−0.014**	−0.013*	−0.033	−0.033	−0.028
Ln (Commuting costs)	0.028	0.021	0.030	0.003	0.000	−0.010	0.019	0.022	0.019	−0.090**	−0.090**	−0.102**
Subway proximity	0.017	0.016	0.007	0.060***	0.062***	0.064***	0.067***	0.061***	0.065***	0.138***	0.137***	0.134***
Ln (Bus routes)	0.018**	0.017**	0.016**	−0.007	−0.007	−0.008	0.002	0.003	0.002	−0.035**	−0.035**	−0.037**
Ln (Bike rental spots)	−0.037**	−0.029**	−0.037***	−0.006	−0.003	−0.010	−0.004	−0.004	−0.008	0.032	0.032	0.019
Ln (Distance to park)	−0.036**	−0.036**	−0.038***	−0.054***	−0.051***	−0.052***	−0.024*	−0.023*	−0.023	−0.014	−0.014	−0.003
Lake proximity	−0.054	−0.050	−0.022	0.034	0.036	0.034	−0.029	−0.030	−0.010	−0.117	−0.117	−0.120
Education facility	0.082***	0.073***	0.080***	0.056***	0.053***	0.059***	0.069***	0.066***	0.068***	0.096***	0.096***	0.102***
Living facility	0.021**	0.019**	0.020***	0.022***	0.019***	0.021***	0.010	0.010*	0.010	−0.018	−0.018	−0.018
Sports facility	0.044***	0.041***	0.042***	0.037***	0.035***	0.035***	0.045***	0.044***	0.043***	0.033***	0.033***	0.030***
Property management	0.056***	0.052***	0.055***	0.018**	0.016*	0.023***	0.072***	0.066***	0.070***	0.056***	0.056***	0.057***
ρ		0.123***			0.098***			0.088***			0.007	
λ			0.217***			0.187***			0.155***			0.130**
Adjusted R^2	0.822	0.834	0.837	0.745	0.755	0.761	0.806	0.813	0.815	0.845	0.855	0.858
LogL	276	309	313	159	177	187	215	233	235	157	157	160
AIC	−555	−613	−620	−272	−306	−329	−383	−418	−424	−268	−266	−273
SC	−435	−488	−501	−148	−177	−205	−258	−288	−299	−178	−172	−183

Note: ***, **, and * represent the statistical significance at 1%, 5%, and 10% level, respectively. The number of Submarket HL, HML, HMH, and HH samples are 1337; 1598; 1676; and 369, respectively. The value of Moran's I of Submarket HL, HML, HMH, and HH samples are 0.510, 0.375, 0.421, and 0.325, respectively.

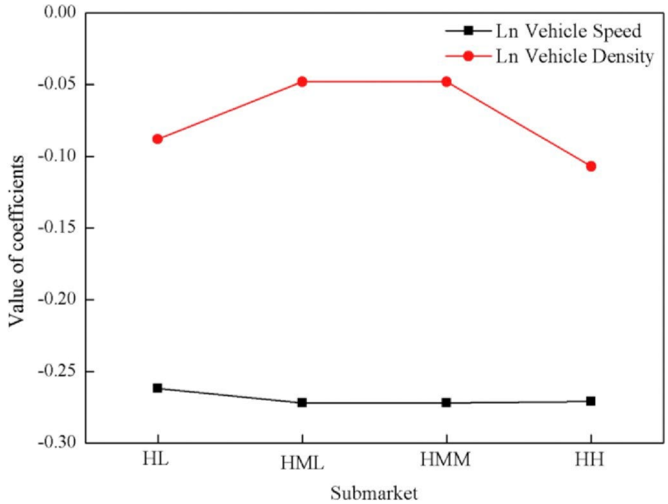

Fig. 2. Vertical pattern of the relationship between road traffic and property price (Submarket H).

literature on the real estate market of China (Sun et al., 2015), we collected these characteristics at the community level. Forth, due to the

Appendix A. Supplementary data

lack of detailed information on street and pedestrian path networks in Hangzhou during our study period, this current study relies on the straight-line distance, which should be improved in the future to obtain more precise estimates. Fifth, in order to obtain comprehensive results, more control variables should be taken into account in the future study. For example, variables control for properties on floors ending in a 4 or an 8 are able to segregate the price premium and discount arise from the superstition of Chinese population.

CRediT authorship contribution statement

Haizhen Wen: Conceptualization, Supervision, Funding acquisition. **Zaiyuan Gui:** Investigation, Formal analysis, Writing - original draft. **Ling Zhang:** Methodology, Funding acquisition. **Eddie C.M. Hui:** Conceptualization, Writing - review & editing, Funding acquisition.

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Appendix

Table A1
PPE distribution summary statistics.

	Overall market	Submarket M	Submarket H	Submarket ML	Submarket MM, MH	SubmarkeHL	Submarket HML	Submarket HMH, HH
Frequency 5%								
	241	284	330	307	324	346	338	359
5–10%	233	265	306	296	312	312	329	338
10–15%	222	260	248	279	287	256	224	260
15–20%	171	175	147	161	156	164	155	136
20–30%	214	148	132	98	99	102	141	118
30–40%	82	58	66	66	47	59	46	41
40–50%	31	30	14	28	16	8	12	4
>50%	63	37	14	22	16	10	12	1
Percentage (%)								
5%	19.173%	22.593%	26.253%	24.423%	25.776%	27.526%	26.889%	28.560%
5–10%	18.536%	21.082%	24.344%	23.548%	24.821%	24.821%	26.173%	26.889%
10–15%	17.661%	20.684%	19.730%	22.196%	22.832%	20.366%	17.820%	20.684%
15–20%	13.604%	13.922%	11.695%	12.808%	12.411%	13.047%	12.331%	10.819%
20–30%	17.025%	11.774%	10.501%	7.796%	7.876%	8.115%	11.217%	9.387%
30–40%	6.523%	4.614%	5.251%	5.251%	3.739%	4.694%	3.660%	3.262%
40–50%	2.466%	2.387%	1.114%	2.228%	1.273%	0.636%	0.955%	0.318%
>50%	5.012%	2.944%	1.114%	1.750%	1.273%	0.796%	0.955%	0.080%
Cumulative percentage (%)								
5%	19.173%	22.593%	26.253%	24.423%	25.776%	27.526%	26.889%	28.560%
10%	37.709%	43.675%	50.597%	47.971%	50.597%	52.347%	53.063%	55.449%
15%	55.370%	64.360%	70.326%	70.167%	73.429%	72.713%	70.883%	76.134%
20%	68.974%	78.282%	82.021%	82.975%	85.839%	85.760%	83.214%	86.953%
30%	85.998%	90.056%	92.522%	90.772%	93.715%	93.874%	94.431%	96.340%
40%	92.522%	94.670%	97.772%	96.022%	97.454%	98.568%	98.091%	99.602%
50%	94.988%	97.056%	98.886%	98.250%	98.727%	99.204%	99.045%	99.920%
Total (%)	100.000%	100.000%	100.000%	100.000%	100.000%	100.000%	100.000%	100.000%

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