https://doi.org/10.1016/j.ufug.2020.126769

The housing market impacts of human activities in public spaces: The case of the square dancing

Yue Xiao[a], Eddie C.M. Hui[b], Haizhen Wen[c,d,*]

[a] School of Public Administration, Zhejiang University of Finance & Economics, Hangzhou, 310018, China [b] Department of Building and Real Estate, Hong Kong Polytechnic University, Hong Kong, China [c] Department of Civil Engineering, Zhejiang University, Hangzhou, 310058, China [d] Center for Real Estate Studying, Zhejiang University, Hangzhou, 310058, China

A B S T R A C T

Square dancing is a popular public activity performed in squares and parks in Chinese cities. Although dancers benefit from such activity physically and mentally, nearby residents may suffer from noise pollution and other negative externalities. However, only a few existing studies have explored the effects of square dancing on the value of residential properties and open spaces. To fill this knowledge gap, this study utilizes the hedonic price model and spatial econometric model to investigate the external effects of square dancing in the housing market of Hangzhou, China. Results show that nearby housing price drops by 5.8 % and 13.0 % when people dance in the nearest park and square. In addition, square dancing decreases the value of parks and squares, and this mediating effect shows spatial heterogeneity (e.g., the premium of living in the segments of 0–200 m and 200 m – 1 km from parks decreases from 0.231 to 0.047 and from 0.126 to 0.045, respectively; the premium of living in the segments of 0–800 m, 800 m – 1.5 km, and 1.5–3 km from squares decreases from 0.157 to 0.060, from 0.165 to 0.022, and from 0.166 to 0.033, respectively). The results of this study indicate that square dancing has a significant negative external effect on housing price and the value of open space. This study offers implications for policy makers to achieve a harmonious society and humanized urban planning. The findings and implications of this study ensure the benefits of residents and improve the value of residential properties and open spaces. In addition, the findings can be generalized across cities or countries where square dancing and other human activities (e.g., night market) are popular.

Keywords:
Square dancing
Housing price
Open spaces
External effects
Spatial econometric model
Hedonic price model

1. Introduction

Square dancing is a common and popular activity in China. Not like the classical style of dance derived from western countries, the square dancing in China is a kind of exercise performed to music for entertainment. Actually, it is created by ordinary people instead of professional dancers with flexible and various dancing elements. One of the most distinct features of square dancing is that, it is usually performed in public open spaces such as parks and squares. The majority of the participants in this Chinese-specific mass dance are the middle-aged and retired women, who are called "dancing grannies" by the Western media. Square dancing is spontaneously organized by the masses. They organize themselves into rank and file and usually dance with music broadcast from an amplifier on wheels. The best dancers are in the front rank to allow others learn from them. People participated in square dancing join different dancing troupes orderly. They occupy public open spaces with shimmying bodies and sometimes turn up the volume of their speakers in a battle to be heard. Up to 100 million people participate in square dancing in China due to its low cost and great enjoyment (China Daily, 2018). Meanwhile, square dancing is also performed in other Western countries by many Chinese, bringing extensive concerns worldwide. It is a social problem that many countries are facing, which deserves more attention from the government and academia.

Mass dancing has a history of thousands of years in China. However, the tension of today′s square dancing may be the product of social change, economic reform, and the "one-child policy." The proportion of urban population has dramatically risen from 17.92 % in 1978 to 58.52 % in 2017 due to the urbanization strategy (China Statistical Yearbook). During these years, a large number of immigrants moved to cities across China. The reform of state-owned enterprises and the early retirement age for Chinese women (50 years old) led to the phenomenon where many middle-aged women do not work nowadays. They no longer need to take care of their large families due to the "one-child policy" enacted in 1982. Thus, numerous retired, idle, and middle-aged women adapt to lives in cities by dancing with their peers.

Parks and squares are the main venues for square dancing. Urban parks are vegetated, natural, and open areas for human recreations. Meanwhile, squares are large open spaces between buildings or streets. Recently, increasing attention has been paid to parks and squares as refuges in high-density urban areas. Many empirical studies have also revealed their implicit value (Shultz and King, 2001; Morancho, 2003; Irwin et al., 2004; Sander and Polasky, 2009). As a typical Chinese city, Hangzhou has many well-preserved urban parks and squares. In particular, square dancing is a prevailing activity in Hangzhou. According to our field survey, 39 out of the 59 parks and 7 of the 12 squares in the six main districts of Hangzhou are venues for square dancing.

Meanwhile, conflicts have arisen among square dancers who pursue simple happiness and nearby residents who want a quiet, private space. In essence, dancers physically and mentally benefit from square dancing. They regard square dancing not only as a regular exercise to stay fit and provide relief from cares, but also as a socialization opportunity to catch up with friends and dispel loneliness and nostalgia. For this reason, square dancing has become increasingly popular in China. However, it also brings discomfort to nearby residents. Noise pollution caused by loud music and people gathering in the morning and evening prevents nearby residents from resting. Several residents think that peacefully asking the dancers to tone down the music is difficult because the dancers believe that the louder the music, the happier.

Unfortunately, less attention has been paid to the influence of human activities on the housing market and open spaces. In fact, housing price is sensitive to externalities caused by human activities (Hughes and Sirmans, 1992). As a typical and important human activity, the effect of square dancing on the value of residential properties and open spaces is uncertain, which deserves further investigation. On the one hand, elderly residents who enjoy square dancing may prefer to live near parks or squares for easy accessibility. Consequently, square dancing may increase the value of parks, squares, and nearby residential properties. On the other hand, square dancing bothers residents living in the vicinity. Nearby residents may suffer from the loud and mixed music. Hence, some of them may no longer want to live next to such parks or squares. In this case, the value of parks, squares, and nearby residential properties decreases because of human activities.

Most existing studies have mainly focused on the static influence of physical attributes of parks and squares, such as distance and area. They concluded that the availability, accessibility, and visibility of parks and squares have added value and significantly increase housing price (Shultz and King, 2001; Morancho, 2003; Irwin et al., 2004; Sander and Polasky, 2009; Jim and Chen, 2010; Hui and Liang, 2016). Housing price also increases as park area increases (Kong et al., 2007; Panduro and Veie, 2013). However, these findings may be biased and inapplicable in cities where people dance in parks and squares nearly every day. Human activities may influence the premium of public facilities on housing price (Troy and Grove, 2008), especially square dancing, which has resulted in complaints and conflicts. Accordingly, the present study innovatively investigates the value of open spaces by attaching importance to the external effect of square dancing under the special context in China.

Adjacent housing units usually share similar public services, natural amenities, and other neighborhood characteristics. Therefore, their prices are correlated with one another. Neglecting the spatial autocorrelation of housing prices may overstate the estimated coefficients of characteristic variables (Wen et al., 2017b). The spatial econometric model can perfectly deal with this problem and should be applied to improve the traditional hedonic price model (LeSage and Pace, 2009, 2010; Elhorst, 2010, 2014; Liang et al., 2018a).

To fill the gaps in existing studies, the present study utilizes the traditional hedonic price model and spatial econometric model to investigate the influence of square dancing on housing price and premium of parks and squares. Hangzhou′s housing transaction data in 2017 were used to answer the following questions. First, how does square dancing affect housing price? Second, how does square dancing affect the premium of parks and squares? Third, does this mediating effect show heterogeneity in different distance segments?

This study is the first to explore the influence of square dancing, which is a typical human activity, on housing price and open spaces in China. The empirical results of this study offer implications for policy makers to achieve a harmonious society and humanized urban planning. The remainder of this paper is structured as follows. Section 2 reviews related studies. Section 3 shows the theoretical framework and put forwards the research hypotheses. Section 4 provides variable definition, model specification, and spatial model selection procedures. Section 5 discusses the empirical results, and Section 6 presents the conclusions and implications of this study.

2. Literature review

2.1. Effects of parks and squares on housing price

Existing studies have investigated the effects of open spaces, such as parks, on housing price. Most of them used the distance from parks to housing units as an explanatory variable to measure the implicit value of park proximity. They found that housing price significantly decreases with the increase in park distance (Shultz and King, 2001; Conway et al., 2010; Jim and Chen, 2010; Tajima, 2010; Wu et al., 2015; Xiao et al., 2019). For every 1% increase in park distance, housing price decreases to varying extents, ranging from 0.052 % (Wen et al., 2015) to 1.6 % (Kong et al., 2007). In addition, several studies have categorized the distance segments to reveal the spatial heterogeneous effects of parks and other open spaces (Munneke and Slawson, 1999; Cho et al., 2011). For example, Cho et al. (2011) found that a developed open space is positively valued in buffers greater than 0.5 miles, forest lands are valued continuously after 1.5-mile buffers, and agricultural lands are negatively valued in all buffers.

Meanwhile, detailed evidence was provided by classifying parks into several categories. Existing studies verified that parks with different sizes show varying effects on housing price. Czembrowski and Kronenberg (2016) indicated that large parks increase housing price most profoundly among 10 other environmental elements. However, no significant influence was found in the effects of medium and small parks. Tajima (2010) demonstrated that the coefficient of a large park distance (−0.085) is nearly twice as big as the coefficient of a small park distance (−0.043). Whereas Espey and Owusu-Edusei (2001) revealed that the greatest influence was found in the distances to small neighborhood parks instead of large parks because of the potential negative effects of being close to large parks (noise and light). Similar results were also obtained by Shultz and King (2001). In addition, other studies classified parks by type or function. For example, Lutzenhiser and Netusil (2001) found that natural parks have the largest added value on housing price in Multnomah County, Portland, followed by specialty and urban parks. Crompton (2005) verified the same sequence of influence of the three types of parks. In addition, Wu et al. (2017a) revealed that community and city park proximity significantly increase housing price, whereas forest park proximity shows a negative effect.

Apart from the traditional measure of distance, scholars have also adopted several new methods to obtain accurate estimates. Kong et al. (2007) utilized a size–distance index to allow the influence of green space distance to vary with size. In addition, Hammer et al. (1974) calculated an accessibility index by adding a constant to park distance and raising them to a negative exponent to prevent undue weight from being placed to housing very next to parks. Furthermore, Wu et al. (2017a) used the gravity model to obtain an objective measure of park accessibility by considering the effects of distance decay, supply, and demand.

Several studies have also revealed the significant effect of open space area on housing price (Lutzenhiser and Netusil, 2001; Conway et al., 2010; Wen et al., 2015). For example, Wen et al. (2015) indicated that a 1% increase in park area raises housing price by 0.008 %.

In fact, only a few studies have investigated the effects of squares on housing price. In particular, Kong et al. (2007) found that the accessibility to squares shows a higher significance than that of accessibility to parks. Every 1% increase in square and park accessibility results in 1.8 % and 1.6 % increases in housing price, respectively.

In general, existing studies have reached a consensus that parks, squares, and other open spaces have significant positive effects on property value. They revealed that being close to parks and squares is regarded as an amenity for which homebuyers are willing to pay. However, most of these studies only investigated the effects of the physical attributes of parks and squares on housing price and neglected the potential external effects of human activities.

2.2. Externalities of human activities on housing price

The housing market is sensitive to externalities caused by human activities and can accordingly adjust housing price (Hughes and Sirmans, 1992). Several studies have explored the externalities brought about by publicly debated issues, such as airport noise (O′Byrne et al., 1985; Cohen and Coughlin, 2008), traffic disturbance (Hughes and Sirmans, 1992; Franck et al., 2015), and air pollution (Harrison and Rubinfeld, 1978; Zheng et al., 2014).

The externality of airports was found to show a considerable effect on the housing market, arousing growing concerns from residents and scholars. Despite the benefits provided by airports, the noise of airplanes drastically decreases nearby housing price (Franck et al., 2015; Trojanek et al., 2017). Houses located in an area with unneglectable airplane noise are sold 20.8 % cheaper than those located elsewhere in Atlanta (Cohen and Coughlin, 2008). In Frankfurt, Germany, every 1 dB increase in aircraft noise results in a 1.7 % decrease in housing price (Winke, 2017).

Moreover, traffic externality negatively influences housing price (Franck et al., 2015; Boennec and Salladarré, 2017). Tian et al. (2017) indicated that the negative effect of transportation system on housing price (e.g., road noise and air pollution) is significantly larger than its positive effect (e.g., convenience and accessibility). Several studies further verified that this traffic penalty shows temporal variance across time series (Wilhelmsson, 2000; Cohen and Coughlin, 2008; Swoboda et al., 2015) and spatial-based effects (i.e., halo effect) (Chasco and Gallo, 2013). In addition, Chasco and Gallo (2015) utilized the quantile conditionally parametric model and found that owners of high-priced housing are more sensitive to traffic noise in Madrid. Meanwhile, railways show a negative effect on the housing market. Diao et al. (2016) determined that the cessation of the operation of railway lines increases the average housing price for affected areas in Singapore by 13.7 %. Dekkers and Straaten (2009) demonstrated that airplane externality exerts the greatest impact on housing price, followed by railway and road traffic.

Unexpectedly, a few studies have obtained contrasting conclusions on the external effect of traffic noise. Jim and Chen (2006) demonstrated that exposure to traffic noise does not affect housing price and homebuyers′ willingness to pay in Guangzhou, China. They attributed the aberrant response to the ubiquity of traffic noise in congested Chinese cities and Chinese people′s low sensitivity and high tolerance to noise. In addition, Hui et al. (2007) found a positive relationship between noise level and housing price in Hong Kong. The reason is that people living in mega high-density cities, such as Hong Kong, tend to sacrifice a quiet living environment for convenience.

Air pollution is another externality that negatively affects housing price. Kim et al. (2003) used the spatial econometric model and found that SO_2 pollution significantly impacts housing price in Seoul. People are willing to pay \$2333 (1.4 % of mean property value) for a 4% decrease in the average SO_2 concentration. Chay and Greenstone (2005) indicated that every 1 μg/m^3 decrease in total suspended particulates increases the average housing price in the U.S. by 0.2 % to 0.4 %. A similar conclusion was also drawn by several studies (Nelson, 1978; Chattopadhyay, 1999; Zabel and Kiel, 2000; Bayer et al., 2009; Boennec and Salladarré, 2017). Attention has been recently paid to the effects of high levels of air pollution on the housing market in China, and the negative externality has also been revealed (Zheng et al., 2014; Chen et al., 2017). However, to the best of our knowledge, the manner in which human activities, such as square dancing, affects housing price has not been examined yet.

2.3. Mediating effects of externalities on open space premium

Although existing studies have investigated the effects of open spaces and externalities of human activities on housing price, less attention has been paid to how such externalities mediate the relationship between open spaces (i.e., parks and squares) and housing price.

Weiss et al. (2011) studied the relationship between the socio-demographic features and neighborhood park availability in New York. They used the geographic information system (GIS) to measure the accessibility of parks. The empirical result showed that urban areas with large African American and Latino populations have better accessibility to parks and facilities. In particular, they further considered the potential influence of disamenities in the neighborhood. They found that this relationship alters after adding the variables of crime rate, pedestrian safety, and noxious land uses to the model. The obvious advantage of park accessibility on such areas is significantly reduced when the region has higher crime rate, lower level of pedestrian safety, and more noxious land uses. Thus, they concluded that the way people utilize and value urban parks can be discounted by the externalities caused by human activities.

Meanwhile, Troy and Grove (2008) explored the intertwined effects of externalities and open spaces on the housing market. They utilized the hedonic price model to investigate how crime level mediates the effects of parks on property value in Baltimore, U.S. Apart from several control variables, they regressed housing price against distance to the nearest park, robbery and rape rates around the park and an interactive term between the two variables. Their results indicated that park proximity increases housing price where robbery and rape rates are lower than a certain threshold rate. However, people value park proximity negatively where crime rates are higher than the threshold. Their study indicated that not all parks are regarded as amenities. Importantly, the externalities of human activities alter the relationship between park proximity and housing price. Obviously, empirical studies cannot merely estimate the value of parks and other open spaces in isolation.

2.4. Hedonic price model considering spatial autocorrelation

Majority of aforementioned studies have utilized the hedonic price model to investigate the effects of open spaces and other factors on housing price. Based on the consumer theory (Lancaster, 1966) and the equilibrium model (Rosen, 1974), the hedonic price model can measure the implicit value of variables of interest by separating several inherent and external characteristics of a commodity. Thus, this method has been extensively used in housing studies (Hammer et al., 1974; Lutzenhiser and Netusil, 2001; Wu et al., 2015, 2017a).

In fact, economic activities or behaviors are based on specific locations, so that they are interacted and corelated spatially. As typical spatial data, housing price is not only affected by its characteristics but also by the prices and characteristics of neighboring houses (Hui and Liang, 2016). Paelinck and Klaassen (1979) emphasized the importance of the explanatory variables in the neighborhood and the spatial autocorrelation as early as 1979. Recently, spatial autocorrelation has also been revealed in several studies (Cohen and Coughlin, 2008; Conway et al., 2010; Tian et al., 2017). However, the spatial autocorrelation of housing prices is not considered in the traditional hedonic price model using the ordinary least squares (OLS). Existing studies using the hedonic price model were based on the assumption that housing prices are independent of one another. Such assumption ignored the spatial autocorrelation of housing price and may lead to biased estimations (Dubin, 2003). Anselin (1988) also indicated that the traditional hedonic price model may lead to biased, invalid or inconsistent estimates due to neglecting the spatial autocorrelation of housing price. Several empirical studies found that the capitalization effects of housing characteristics are exaggerated without controlling the spatial attributes of housing price (Long et al., 2009; Liao and Wang, 2012; Wen et al., 2017a). Thus, it is necessary to test and control the spatial autocorrelation of housing data so as to get unbiased and accurate estimations.

The spatial econometric model can deal with the spatial attributes of housing price and improve the traditional hedonic price model. Hui et al. (2007) utilized the OLS model, spatial autoregression model (SAR), and spatial error model (SEM) to explore the neighborhood and environmental effects on housing price. They found that SEM has better explanatory power and thus is more appropriate and reliable for analyzing the data. Similarly, Trojanek et al. (2017) used the OLS, SAR, and SEM to study the effect of aircraft on housing price and found a strong evidence on the existence of spatial autocorrelation. In addition, they indicated that the spatial econometric model is more robust than the OLS method. The necessity of using the spatial econometric model has also been emphasized in several other studies (Cho et al., 2006; Cohen and Coughlin, 2008; Conway et al., 2010; Tian et al., 2017; Hui et al., 2018). For instance, Wen et al. (2017b) found that housing price in Hangzhou portrays a significant spatial autocorrelation, which further verifies the necessity of using the spatial econometric model.

In fact, growing number of studies in China have utilized the spatial econometric model to investigate the effect of open spaces (e.g., park and green space) on the housing market over the past decade. The importance of spatial attributes in the real estate market in China is better understood, although such studies are still fewer than those in the western countries. The spatial lag model and the spatial error model were widely used by Chinese scholars. For example, Du and Huang (2018) used these two models to control the influence of spatial autocorrelation brought by adjacent housing price and by neighborhood factors in the residuals. They found that every 1 km close to the wetland park leads to 195 CNY/m^2 increase in housing price in Hangzhou, China. This amenity value is higher in bust period than that in boom period. They indicated that the spatial autocorrelation of housing price affects the estimated value of wetland park and neglecting this spatial attribute would bias the empirical result. Wu et al. (2018) used the spatial lag model and the spatial error model to study the effect of different land uses on housing price in Beijing, China. They revealed that the accessibility of open space significantly increases housing price and the spatial econometric model improves the hedonic price analysis. Also, the spatial lag model and the spatial error model were used to measure the implicit value of open space on land price. Qu et al. (2020) verified the necessity of using the spatial econometric model because land price is spatially corelated. They utilized the spatial lag mode and the spatial error model to investigate the factors that influencing land price. The empirical results of spatial lag model were interpreted because it has better explanatory power. They found that park accessibility, waterfront and other factors are significantly capitalized into land price and this capitalization effect increases over time. Similarly, Wu et al. (2017b) indicated that land price is likely to be corelated with the prices and characteristics of neighboring lands. Thus, the spatial error model was used to measure the implicit value of several urban amenities. They found that the spatial error model enhances the model fit of the hedonic price model. Every 1% increase in the distance to green space increases 0.41 % of land price after controlling the spatial autocorrelation.

In addition, the spatial Durbin model (SDM) was used by a few studies to control the spatial attributes of housing price and further partition the direct and indirect effects of open spaces. Hui and Liang (2016) used the spatial Durbin model and found a significant feedback effects of landscape views from neighbors in Guangzhou, China. Park view shows an amenity effect on housing price and the indirect effect constitutes 32 % of the total effect. Hui et al. (2012) used the SDM to deal with the spatial correlation between housing prices and revealed the heterogeneous effects of landscape views on different floor levels. They found that public or estate park view increases housing price and provides a steady amenity value for housing in low, medium and high floors.

A few studies used the geographically weighted regression (GWR) model to further explore the spatial non-stationary influence of open space. Yuan et al. (2018) used the hedonic price model and the GWR to estimate the effects of amenities and policy change on housing price. They found that park distance is negatively related to housing price and this relationship shows spatiotemporal heterogeneity. Wu and Dong (2014) used locally weighted regression (LWR) model and found that every 1% decrease in the distance to the nearest park increases land price by 0.67 % and this proximity premium is larger in the suburb than that in the city center. Liang et al. (2018b) used the GWR and revealed the spatial heterogeneous amenity value of parks in Ningbo, China.

Several other forms of spatial econometric model were used by Chinese scholars. For example, Liao and Wang (2012) incorporated spatial econometric model and the quantile regression model to investigate the effects of housing attributes on the whole conditional distribution of housing price. By doing so, the explanatory ability of the hedonic price model is enhanced. They found that the coefficient of distance to park shows a downward trend in the conditional distribution of housing price and a discount is observed in lower quantiles. Wu et al. (2017a) used the geographical detector method to deal with the spatial effect and indicated that park accessibility is an important factor influencing housing price. Jiao and Liu (2010) used a spatial hedonic method based on the geographic field model (GFM) to explore the value of parks. They found that city-level parks significantly increase housing price while district-level parks do not, indicating the importance of large and multifunctional parks.

In general, increasing attention has been paid to the spatial autocorrelation of housing and land prices in China. These studies mainly focused on the distance and other static attributes of open spaces so as to reveal their amenity value. Actually, human activities are supposed to influence the housing market (Hughes and Sirmans, 1992). However, less attention has been paid to the externalities caused by human activities in open space, which may result in biased estimations. Thus, this study fills the gap in existing studies by considering the spatial autocorrelation of housing price and the externalities of square dancing (a popular activity in most parks and squares in China). The spatial econometric model is used to reveal the influence of such recreational activity on housing price and the value of open space.

3. Theoretical background and hypotheses

Square dancing has become increasingly popular in China. However, it may also bring external effects. Referring to the theory of cost and benefit of externalities, Fig. 1 shows the logic behind this study. This mechanism may be better illustrated by connecting empirical study with theory. In this way, the externalities of square dancing can be better understood and its importance in urban management would be revealed. Although this theory does not strictly aim at the externalities of human activities, it can also provide valuable evidence for deep thinking and research. To be specific, square dancing can be of benefit to the society and individuals (e.g., physical and mental health improvements), which is represented by the social benefit. On the other hand, the cost of dancers (e.g., travel time and expense) is known as the private cost. The social cost further includes the negative externalities

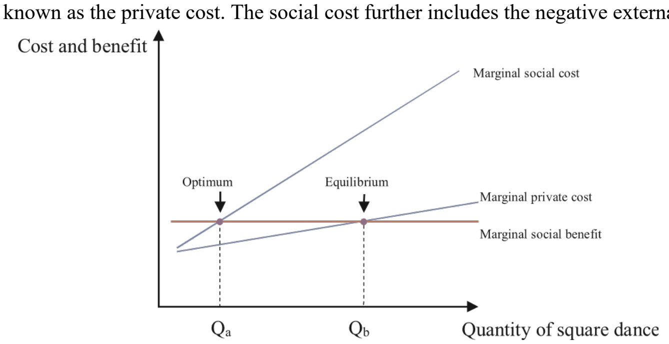


Fig. 1. Cost and benefit of square dancing.

that square dancing might bring (to be tested). As shown in Fig. 1, with the increase in the quantity of square dancing, marginal social cost is expected to significantly increase due to the growing noise pollution and other unwanted nuisances, while the increase in marginal private cost is mild. Meanwhile, the marginal social benefit remains steady with the change in the quantity of square dancing. The "optimum" and "equilibrium" (also known as "social optimum" and "private optimum") are reached in the two intersections of the three lines in the figure. Q_b (when "equilibrium" is reached) is significantly larger than Q_a (when "optimum" is reached). Thus, if the negative externalities of square dancing exist (to be tested), then its quantity (or impact) should at least be reduced to Q_a to achieve the optimum between cost and benefit. Conversely, if negative externalities are not tested in this study, then controlling for square dancing is unnecessary because the "equilibrium" equals to the "optimum".

In addition, the benefit of open space accessibility might be influenced by square dancing. As illustrated in Fig. 2, the x axis indicates the distance between housing and open spaces; the y axis indicates the benefit or loss of people living there. Fig. 2a illustrates that if no one dances in open spaces, the benefit of living next to it (e.g., open view, pleasant landscapes and clean air, etc.) is considerable. With the increase in the distance between housing and open spaces, the benefit of residents gradually decreases (shown as the line benefit). On the other hand, living adjacent to open spaces also faces several unwanted nuisances (e.g., noise, light and crime, etc.), which may cause potential loss to nearby residents (shown as the line loss). Generally, the loss is smaller than the benefit, especially for those living near open spaces. Residents living in different distance segments still gain pure benefit (shown as the dotted area). However, when people dance in open spaces, the negative externalities may bring additional loss to residents living nearby. Thus, the loss line becomes steeper in Fig. 2b. Consequently, the pure benefit decreases and those who live next to open spaces lose the most.

As far as we know, none of the existing studies have theoretically and empirically investigated the influence of square dancing on housing price and open spaces (i.e., parks and squares). To fill this research gap, the following hypotheses are put forward to explore this influence in depth:

H1. Parks and squares have added value on nearby housing price.

Square dancing is usually performed in parks and squares in most Chinese cities. Many studies have indicated that parks and squares show positive effects on housing price (Shultz and King, 2001; Morancho, 2003; Irwin et al., 2004; Kong et al., 2007; Sander and Polasky, 2009). Consequently, parks and squares are assumed to have added value on housing price in Hangzhou, which is the premise of the following hypotheses.

H2. Square dancing negatively affects adjacent housing price.

Although none of existing studies have explored the influence of square dancing, several news reports already revealed the potential negative effects of square dancing on housing price. Noise pollution may bother nearby residents, and this kind of housing is not welcomed in the housing market. Consequently, square dancing is assumed to impair the value of nearby properties.

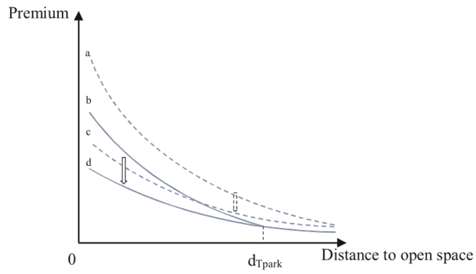
In addition, dancing in parks and in squares may show different influence patterns on housing price. The reason is that the average area of squares is much larger than that of parks, such that more people gather in the latter. Also, parks with more green landscapes provide fewer open spaces compared with squares, which are spacious and broad. Thus, more dancing troupes perform in squares, which may show a more profound effect on the housing market.

H3. Square dancing impairs the value of parks and squares.

As H1 points out, homebuyers are supposed to pay for the amenity value of nearby parks or squares. However, this perspective may alter when human activities, which cause trouble or inconvenience to nearby residents, are taken into consideration. Under this circumstance, the premium of park and square proximity may decrease due to the negative external effect of square dancing.

H4. Square dancing shows heterogeneous mediating effect on the premium of parks and squares in different distance segments.

If square dancing impairs the premium of parks and squares, this mediating effect may show heterogeneity in different distances between housing units and parks or squares. As illustrated in Fig. 3, the premium of squares (or parks) may decrease from line a to line c (or from line b to line d) when there are dancing events. Meanwhile, as dancing in parks is supposed to show less influence, we assume that its mediating effect may disappear after the distances to parks are larger than a certain



(a) Squares without dancing events. (b) Parks without dancing events. (c) Squares with dancing events. (d) Parks with dancing events.

Fig. 3. Changes in the premium of park and square proximity in accordance with H3 and H4.

threshold (d_{Tpark} in Fig. 3).

4. Data and model

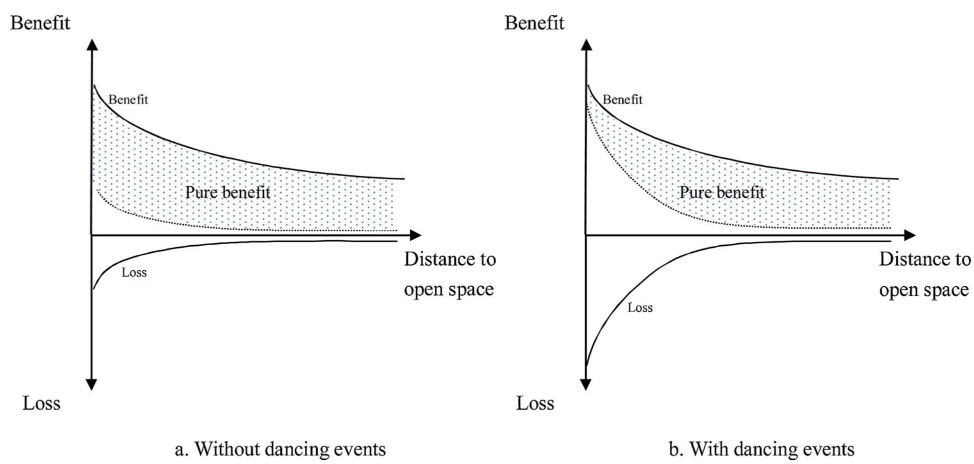


Fig. 2. Benefit and loss of living in different distance segments to open space.

4.1. Study area, data, and variable

Hangzhou, the capital of Zhejiang Province, is selected as the study area. Hangzhou is not only the political and economic center of the province but also a famous tourist city with abundant natural resources. It is renowned as a paradise because of many world-famous natural sights and pleasant living environment. A large number of urban parks and squares have been developed and well preserved in Hangzhou. The six main districts (XH, SC, XC, GS, JG, and BJ) in Hangzhou are selected as the study areas. 59 parks and 12 urban squares can be found in the study area. Actually, square dancing has become one of the most popular daily activities in Hangzhou, and well-developed parks and squares in the city appeal to a growing number of dancers. According to our field survey, 39 out of the 59 parks and 7 of the 12 squares in the six main districts are the places where people dance. Thus, it is a desirable study area for conducting a comprehensive research on the influence of square dancing on the housing market. Fig. 4 plots the study area, where stars indicate the observations (housing communities), blue circles indicate the parks (several big parks are illustrated as large blue circles), yellow squares indicate the urban squares, and three big urban squares are shown in the large icons.

The housing transaction data in 2017 were obtained through a real estate agency in Hangzhou. The average housing price at the community level was utilized as the dependent variable. Only multi-storey and high-rise buildings were adopted to prevent potential problems caused by an inconsistent dataset. Abnormal observations (e.g., incomplete observations and outliers out of the three times the standard deviation of the sample mean) were discarded to ensure reliable results. After preprocessing of the dataset, a total of 505 housing observations were used. Actually, the housing market in China is mainly constitute of communities with several buildings sharing the same interior infrastructure and service. Housing in the same community usually show similar unit prices because their structure, location and neighborhood characteristics are almost the same. Housing price at community level is one of the most important factors referred by homebuyers when making housing purchase decisions. Thus, it is widely used in many studies conducted in Chinese cities and most of these studies obtained reliable results. Similar to this study, they mainly obtained around 200–600 observations (Kong et al., 2007; Zheng et al., 2016; Wen et al., 2018, 2019; Liang et al., 2018a), indicating that the sample size in this study is relatively reasonable.

Referring to the hedonic framework, one structure characteristic, one location characteristic, and eight neighborhood characteristics were utilized as independent variables. Table 1presents the definitions of variables in this study. Building age of each community was used as the structure characteristic and was obtained through the real estate agency. West lake is the traditional CBD in Hangzhou, attracting many citizens and tourists. Thus, the distance to West Lake was adopted as location characteristic and was measured by Google Maps.

Comprehensive work has been done to supplement the neighborhood characteristics of housing observations. The facilities and services provided in each community are related to residents' daily life and may affect housing price. Thus, green condition was used to describe the quality and quantity of the green environment inside each community (e.g., grass lawn, trees and other green landscapes). The quality and quantity of sports facilities and the quality of property management service in each community were also controlled. The improvement in such facilities and services may increase housing price to some extent. These variables were obtained through a survey on 660 communities in the study area. The interior environment and services of these communities were measured through a questionnaire and a field investigation. 20 residents in each community were selected as the respondents to score the variables. The average score was calculated and adjusted according to our field investigation. The final score was then considered as the variable value (i.e., green condition, sports facilities, and property management). In addition, the public transit services nearby were measured by Google Maps to reflect the traffic convenience of each community, such as the number of bus routes within 1 km of a community and the distance to the nearest subway station. Also, educational facilities and potential disamenity (distance to rubbish transfer station) around each community were considered and measured by Google Maps. Moreover, the distances to and areas of parks and squares were measured by Google maps to investigate the influence of parks and squares on housing price.

As for the dancing variables, a field survey was conducted to investigate whether people dance in a park or square ($Dance_{in\ park}$ and $Dance_{in\ square}$). We first did a pilot investigation using the internet. Actually, several internet forums (e.g., Dazhongdianping and 19 Lou) contain the details of majority of parks and squares in Hangzhou. Also, comments on these open spaces from citizens or tourists (some are related with dancing events) can be found in these online resources. Consequently, this information was collected and used to preliminarily check whether people dance in a park or square. Then, a field survey covering the parks and squares in the study area was conducted. We stayed in a park or square during morning (7:30–9:30 a.m.) and evening (18:30–20:30 p.m.) for three consecutive days (the investigation was put off to the next day if it rains) to confirm whether people dance there. Then, dummy variables of $Dance_{in\ park}$ and $Dance_{in\ square}$ were measured. If square dancing was observed in the nearest park or square of a community, the corresponding variable equals to 1, otherwise it is 0. Table 2 provides the statistic description of variables.

4.2. Model specification

The hedonic price model and spatial econometric model were used to investigate the effects of square dancing on housing price and premium of parks and squares. After a series of preliminary tests, we find that the hedonic price model with a logarithmic form has the best model fit. In other words, it can interpret the relationship between housing price and explanatory variables better than other model forms. Consequently, the basic model (M1) is designed as follows: $ln\boldsymbol{P} = +\alpha_0$ $\alpha\ ln_1 \boldsymbol{S} + \beta\ ln_1 \boldsymbol{L} + \gamma_j \boldsymbol{N}_j + \varphi\ ln_k \boldsymbol{N}_k + \theta\ ln_1 \boldsymbol{D_{park}} + \theta\ ln_2 \boldsymbol{S_{park}}$

$$+ \theta\ ln_3 \boldsymbol{D_{square}} + \theta\ ln_4 \boldsymbol{S_{square}} + \varepsilon, \qquad (1)$$

Where P refers to the housing price; S denotes the structure characteristic; L indicates the location characteristic; N_j pertains to the discrete neighborhood characteristics; N_k represents the continuous neighborhood characteristics; D_{park}andD_{square} are the distances from a community to its nearest park and square, respectively; S_{park} and S_{square} are the areas of the nearest park and square, respectively; α_0, α_1, β_1, γ_j, φ_k, and $\theta_{1,2,3,4}$ are the coefficients to be estimated; and ε is the error

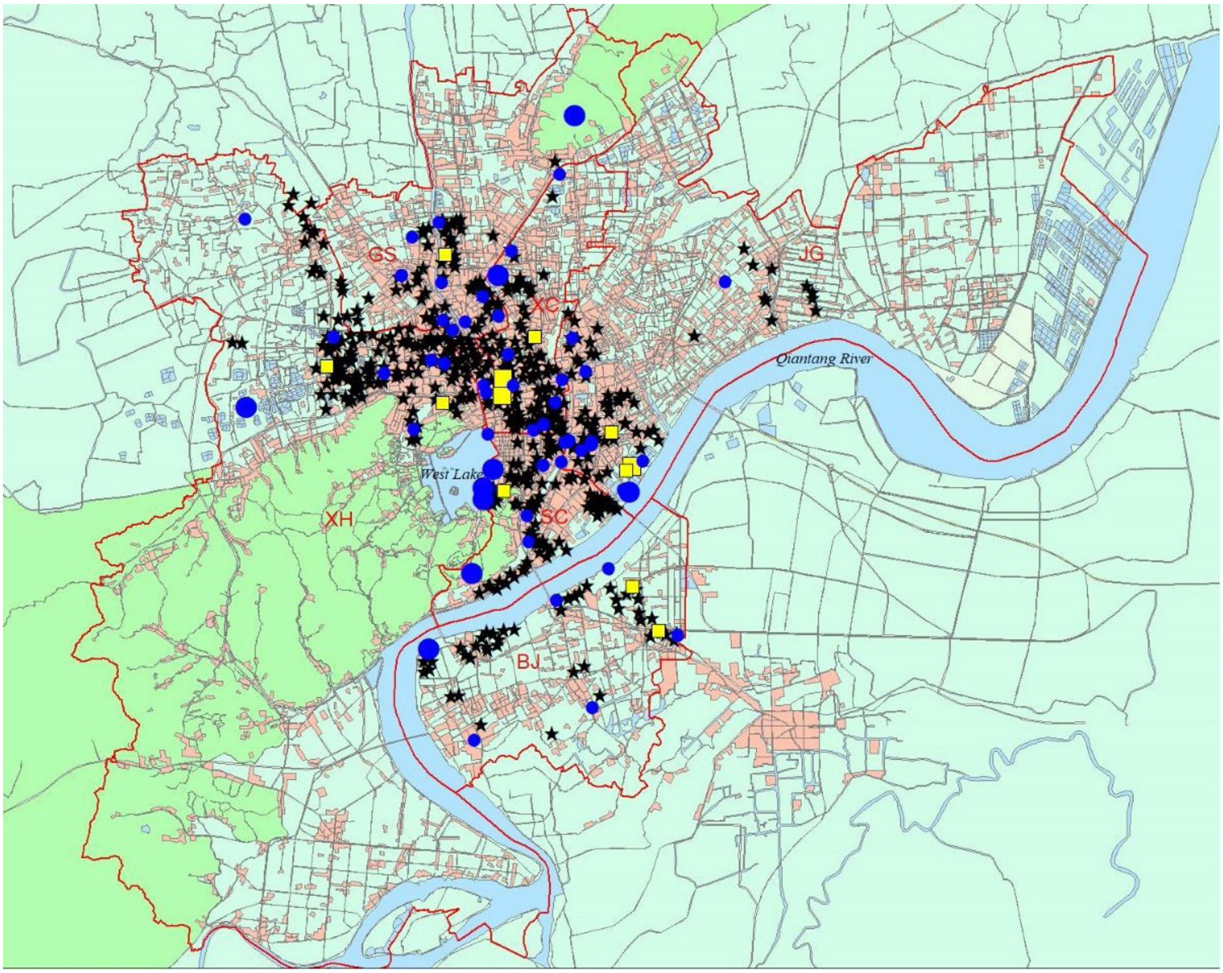


Fig. 4. Study area.
Stars = housing observations; blue circles = parks; large blue circles = big parks; yellow squares = urban squares and large yellow squares = big urban squares.

term.

Then, two dummy variables were added in the basic model to test whether a significant effect of square dancing on housing price is observed. This model (M2) takes the following form:

$$ln\boldsymbol{P} = +\alpha_0 \quad \alpha\ ln_1 \boldsymbol{S} + \beta\ ln_1 \boldsymbol{L} + \gamma_j \boldsymbol{N}_j + \varphi\ ln_k \boldsymbol{N}_k + \theta\ ln_1 \boldsymbol{D}_{park} + \theta\ ln_2 \boldsymbol{S}_{park} + \theta\ ln_3 \boldsymbol{D}_{square} + \theta\ ln_4 \boldsymbol{S}_{square} + \theta_5 \boldsymbol{Dance}_{in\ park} + \theta_6 \boldsymbol{Dance}_{in\ square} + \varepsilon, \quad (2)$$

Table 1
Variable definition.

	Variables	Variable definition	Expected sign
Explained variable	P	Average price of a community (CNY/m^2)	/
Structure characteristic	Age	Age of a community (year). The age of a community built in 2017 is 1	–
Location characteristic	West Lake distance	Straight-line distance from the center of a community to the coast of West Lake (km)	–
Neighborhood characteristics	Green condition	Score of green condition in a community divided into five grades, namely, very good (5 scores), good (4 scores), general (3 scores), poor (2 scores), and very poor (1 score)	+
	Sports facilities	Quality and quantity of sports facilities in a community divided into five grades, namely, very good (5 scores), good (4 scores), general (3 scores), poor (2 scores), and very poor (1 score)	+
	Property management	The quality of the property management service of a community divided into five grades, namely, very good (5 scores), good (4 scores), general (3 scores), poor (2 scores), and very poor (1 score)	+
	Bus route	Number of bus routes within 1 km of a community	+
	Subway distance	Straight-line distance from the center of a community to the nearest subway station (km)	–
	Nearby university	Dummy variable is 1 if a university can be found within 1 km of a community; otherwise, it is 0	+
	Educational facilities	Kindergarten, primary school, junior high school, and senior high school within 1 km of a community; each one is scored 1 for a total of 4 scores	+

	DRTS	Straight-line distance from the center of a community to the nearest rubbish transfer station (km)	+
Dance characteristics	D_{park}	Straight-line distance from the center of a community to the nearest park (km)	−
	S_{park}	Area of the nearest park of a community (hectare)	+
	D_{square}	Straight-line distance from the center of a community to the nearest square (km)	−
	S_{square}	Area of the nearest square of a community (hectare)	+
	$Dance_{in\ park}$	Dummy variable is 1 if people dance in the nearest park of a community; otherwise, it is 0	−
	$Dance_{in\ square}$	Dummy variable is 1 if people dance in the nearest square of a community; otherwise, it is 0	−

Table 2
Statistic description.

Variables	Minimum	Maximum	Mean	Standard error	N
P	14,195.40	96,642.57	29,346.88	9,483.28	505
Age	5.00	37.00	15.91	6.89	505
West Lake distance	0.45	13.10	4.11	2.28	505
Green condition	1.00	5.00	3.07	1.12	505
Sports facilities	1.00	5.00	1.83	1.27	505
Property management	1.00	5.00	2.57	1.28	505
Bus route	2.00	70.00	31.02	14.67	505
Subway distance	0.10	6.90	1.12	1.07	505
Nearby university	0.00	1.00	0.59	0.49	505
Educational facilities	1.00	4.00	3.13	0.75	505
DRTS	0.08	13.22	4.98	2.90	505
D_{park}	0.06	4.15	0.85	0.62	505
S_{park}	0.10	346.00	7.59	35.54	505
D_{square}	0.16	9.45	2.03	1.61	505
S_{square}	1.68	187.66	24.15	31.26	505
$Dance_{in\ park}$	0.00	1.00	0.65	0.48	505
$Dance_{in\ square}$	0.00	1.00	0.62	0.48	505

Where $Dance_{in\ park}$ and $Dance_{in\ square}$ indicate whether people dance in the nearest parks or squares, respectively; θ_5 and θ_6 are the coefficients to be estimated. The remainder of the variables are similar to those in Eq. (1).

Next, interactive terms ($Dance_{in\ park}*\ln D_{park}$, $Dance_{in\ park}*\ln S_{park}$, $Dance_{in\ square}*\ln D_{square}$, and $Dance_{in\ square}*\ln S_{square}$) are added in Eq. (2) in the following sequence: M3–M6 to explore whether square dancing has a mediating effect on the premium of parks and squares. The last model (M7) contains all interactive terms and is structured as follows:

$$\begin{aligned} ln\boldsymbol{P} = +\alpha_0 \quad & \alpha\, ln_1 \boldsymbol{S} + \beta\, ln_1 \boldsymbol{L} + \gamma_j \boldsymbol{N}_j + \varphi\, ln_k \boldsymbol{N}_k + \theta\, ln_1 \boldsymbol{D_{park}} + \theta\, ln_2 \boldsymbol{S_{park}} \\ & + \theta\, ln_3 \boldsymbol{D_{square}} + \theta\, ln_4 \boldsymbol{S_{square}} + \theta_5 \boldsymbol{Dance_{in\ park}} + \theta_6 \boldsymbol{Dance_{in\ square}} \\ & + \theta_7 \boldsymbol{Dance_{in\ park}} * ln\boldsymbol{D_{park}} + \theta_8 \boldsymbol{Dance_{in\ park}} \times ln\boldsymbol{S_{park}} \\ & + \theta_9 \boldsymbol{Dance_{in\ square}} \times ln\boldsymbol{D_{square}} + \theta_{10} \boldsymbol{Dance_{in\ square}} \times ln\boldsymbol{S_{square}} \\ & + \varepsilon, \end{aligned} \quad (3)$$

Where $\theta_{7,\ 8,\ 9,10}$ are the coefficients to be estimated. The remainder of the variables are similar to those in Eq. (2).

In addition, different distance segments from a community to the nearest park or square and corresponding interactive terms were added to further reveal the heterogeneous effect of square dancing on the premium of parks or squares. Distances to parks and squares were classified into four categories (DP_m and DS_n), including the region very near parks and squares, near but not very close to parks and squares, farther region, and the region very far away from parks and squares. According to the statistic description of park distance and square distance, 0–200 m ($DP_{0–0.2}$), 200 m – 1 km ($DP_{0.2–1}$), 1–3 km ($DP_{1–3}$), and 3 km above (DP_{3+}) were selected to distinguish different segments of park distance. Meanwhile, the average square distance is slightly larger than the average park distance, such that 0–800 m ($DS_{0–0.8}$), 800 m –
1.5 km ($DS_{0.8–1.5}$), 1.5–3 km ($DS_{1.5–3}$), and 3 km above (DS_{3+}) were used. The models (M8–M10) are respectively designed as follows:

$$\begin{aligned} ln\boldsymbol{P} = +\alpha_0 \quad & \alpha\, ln_1 \boldsymbol{S} + \beta\, ln_1 \boldsymbol{L} + \gamma_j \boldsymbol{N}_j + \varphi\, ln_k \boldsymbol{N}_k + \theta\, ln_2 \boldsymbol{S_{park}} + \theta\, ln_3 \boldsymbol{D_{square}} \\ & + \theta\, ln_4 \boldsymbol{S_{square}} + \delta_m \boldsymbol{DP}_m + \mu_m \boldsymbol{Dance_{in\ park}} \times \boldsymbol{DP}_m + \varepsilon \end{aligned} \quad (4)$$

$$lnP = +\alpha_0 \quad \alpha\, ln_1 \boldsymbol{S} + \beta\, ln_1 \boldsymbol{L} + \gamma_j \boldsymbol{N}_j + \varphi\, ln_k \boldsymbol{N}_k + \theta\, ln_1 \boldsymbol{D}_{park} + \theta\, ln_2 \boldsymbol{S}_{park}$$

$$+ \theta\, ln_4 \boldsymbol{S}_{square} + \sigma_n \boldsymbol{DS}_n + \tau_n \boldsymbol{Dance}_{in\ square} \times \boldsymbol{DS}_n + \varepsilon \quad (5)$$

$$lnP = +\alpha_0 \quad \alpha\, ln_1 \boldsymbol{S} + \beta\, ln_1 \boldsymbol{L} + \gamma_j \boldsymbol{N}_j + \varphi\, ln_k \boldsymbol{N}_k + \theta\, ln_2 \boldsymbol{S}_{park} + \theta\, ln_4 \boldsymbol{S}_{square}$$

$$+ \delta_m \boldsymbol{DP}_m + \sigma_n \boldsymbol{DS}_n + \mu_m \boldsymbol{Dance}_{in\ park} \times \boldsymbol{DP}_m + \tau_n \boldsymbol{Dance}_{in\ square}$$

$$\times \boldsymbol{DS}_n + \varepsilon, \quad (6)$$

Where δ_m, σ_n, μ_m, and τ_n are the coefficients to be estimated and the rest of the variables are similar to those in the above equations.

4.3. Spatial econometric model selection procedures

As mentioned in the literature review, housing price may be spatially correlated and this spatial attribute cannot be controlled by using the traditional hedonic price model only. Thus, it is necessary to test the spatial autocorrelation of housing price, and then, to choose suitable spatial econometric models. In this way, the traditional hedonic price estimation can be improved and reliable conclusions would be drawn.

Existing studies suggested that a series of tests can be run for model selection (Anselin, 2004; Mur and Angulo, 2009; Hui and Liang, 2016). This method is known as the specific-to-general method (Hendry, 1995) starting from the OLS model. Several tests are conducted to check whether this standard model need to be extended to spatial models. This study follows the selection procedure suggested by the abovementioned studies. First, the Moran′ I index of housing price was calculated. Moran′ I measures the spatial autocorrelation of housing sample (Anselin, 1988) and ranges from -1 to 1. A significant and positive Moran′ I means housing prices are positively corelated, and vice versa. As suggested by Lesage (1999), testing the Moran′ I index of the dataset is the first step to choose the spatial econometric model. In this study, the Moran′ I is 0.2054 and is significant under the 1% significance level. This result indicates that housing prices in the study area are positively corelated with each other and the spatial econometric model should be adopted. Next, the LM Lag and LM Error of each model were calculated to check whether the spatial lag model or the spatial error model is more appropriate (Elhorst, 2010). Given the limited space, the result of M1 is discussed here since other models show similar testing result. As Table 3 shows, LM Lag and LM Error are significant under the 1% significance level, indicating the necessity to conduct Robust tests. Thus, Robust LM Lag and Robust LM Error were further tested. The result (Table 3) shows that both of them are significant under the 5% significance level. Robust LM Lag equals to 5.652 and Robust LM Error equals to 5.036. Thus, the model with larger test statistics is favored (Anselin, 2004). Since the Robust LM Lag and Robust LM Error are close to each other, both spatial lag model (SLM) and spatial error model (SEM) were adopted in the empirical study to deal with the spatial autocorrelation of housing price and the one with better test statistics would be interpreted (Hui and Liang, 2016).

SLM assumes that housing price is not only influenced by its characteristics but also by the prices of the neighboring housing. It takes the following form:

$$lnP = \rho W\, Pln + +\beta X \quad \varepsilon. \quad (7)$$

SEM considers the spatial autocorrelation in the residuals and is structured as follows:

$$lnP = +\beta X \quad u, \quad (8)$$

$$u = \lambda W u + \varepsilon, \quad (9)$$

Table 3
Diagnostics for spatial dependence.

Test	Statistical Value	P-Value
Lagrange Multiplier (lag)	20.671	0.000
Lagrange Multiplier (error)	20.055	0.000
Robust LM (lag)	5.652	0.017
Robust LM (error)	5.036	0.025

Where P is the housing price; X denotes the characteristic variables; β is the regression coefficients; ρ indicates the spatial autoregression coefficient; λ represents the spatial autoregression coefficient of residual; and W refers to the spatial weight matrix, which represents the spatial relationship among sample points.

W has several forms, such as distance, binary contiguity, and knearest matrixes. The binary contiguity matrix is suitable for spatial data distributed as continuous planes, which is commonly used in regional economic research. However, the housing observations of this study are scattered over the whole study area. It is difficult to determine whether each two of them share a common vertex or border. Thus, the binary contiguity matrix is not suitable for this study. On the other hand, nearest k observations around the designated observation i are required for the k-nearest matrix. Since k is set exogenously, the parameters need to be further optimized and a series of sensitivity analyses are necessary to get a reliable estimation. The distance weight matrix has advantages in robustness and calculation efficiency, which is a method commonly used in many empirical studies (Hui and Liang, 2016). Therefore, this study used the distance weight matrix to interpret the spatial relationship between observations. According to the First Law of Geography, adjacent housing may have spatial correlation. The closer the housing are, the more significant the interaction will be. Based on this theory, the distance weight matrix uses the reciprocal of spatial distance to explain their spatial relationship that decays with the increase in distance. We also tried the distance weight matrix using the order of twice and third power of the distance, while their estimates are not as good as that of the matrix with a reciprocal term. Consequently, the distance matrix with the following form is utilized in this study:

$$W_{ij} = \frac{1}{d_{ij}} \quad (10)$$

Where d_{ij} is the Euclidean distance between observation i and observation j. When i=j, W_{ij}=0. The spatial weight matrix is row-standardized.

5. Results and discussion

5.1. Effects of parks and squares on housing price

Table 4 presents the results of the basic model. As for the OLS result in column 1, the adjusted R^2 is 0.518, which indicates that this model has a relatively good explanatory power. Most independent variables are significant at the 10 % significance level with expected signs. In particular, park and square proximity and park area significantly increase housing price.

As discussed above, the dataset portrays significant spatial autocorrelation and this is further supported by the results of spatial econometric models. Columns 2 and 3 in Table 4 show that both spatial autoregression coefficients in SLM and SEM are significant (rho = 0.224 and lambda = 0.763). The adjusted R^2 of SLM and SEM are improved to 0.535 and 0.529, respectively. These results indicate that the models considering the spatial autocorrelation of housing prices are better than the traditional hedonic price model. The statistic of Log likelihood, Akaike info criterion and Schwarz criterion of SLM (which are 125.64, −219.279, and −151.686, respectively) are better than those of SEM (which are 118.917, −207.833, and −144.465, respectively). The test statistics consistently show that the Robust LM lag is a bit more significant than Robust LM error. Thus, SLM better describes the dataset. Other models in the empirical study show the same test statistic results. Thus, this study mainly interprets SLM results in the following parts.

In particular, the regression result of SLM shows that the coefficients of Ln D_{park}, Ln D_{square} and Ln S_{park} are significant with value of −0.034, −0.042 and 0.012, indicating that people show certain willingness to pay for living close to parks (especially larger parks) and squares. According to Kim et al. (2003); Cohen and Coughlin (2008) and

Table 4
Results of M1.

Variables	OLS (1)		SLM (2)		SEM (3)	
	Coe.	Sig.	Coe.	Sig.	Coe.	Sig.
Constant	10.516***	0.000	8.205***	0.000	10.521***	0.000
Ln Age	−0.100***	0.001	−0.103***	0.000	−0.103***	0.000
Ln West Lake distance	−0.295***	0.000	−0.274***	0.000	−0.302***	0.000
Green condition	0.020*	0.089	0.023*	0.052	0.018	0.116
Ln Bus route	−0.044*	0.053	−0.041*	0.072	−0.051**	0.029
Ln Subway distance	−0.059***	0.000	−0.053***	0.000	−0.056***	0.000
Nearby university	0.076***	0.000	0.070***	0.000	0.078***	0.000
Educational facilities	0.041***	0.002	0.037***	0.004	0.041***	0.001
Sports facilities	0.036***	0.000	0.034***	0.000	0.036***	0.000
Property management	0.047***	0.000	0.045***	0.000	0.049***	0.000
Ln DRTS	0.069***	0.000	0.066***	0.000	0.076***	0.000
Ln D_{park}	−0.035**	0.014	−0.034**	0.015	−0.034**	0.015
Ln S_{park}	0.014**	0.041	0.012*	0.071	0.014**	0.034
Ln D_{square}	−0.045***	0.002	−0.042***	0.003	−0.038**	0.012
Ln S_{square}	−0.007	0.461	−0.004	0.705	−0.005	0.617
Rho			0.224**	0.048		
Lambda					0.763***	0.000
Adj-R^2	0.518		0.535		0.529	

***, **, and * represent the 1%, 5%, and 10 % significance levels, respectively.

Steimetz (2010), a spatial multiplier should be considered to accommodate the potential spillover effect from neighbors in spatial lag model. By doing so, the total impact on HP_i including the induced effects of a neighborhood′s housing characteristic change can be explained (Kim et al., 2003). The spatial multiplier takes the form of $(I - \rho W)^{-1}$ and transforms to $(1-\rho)^{-1}$ when the spatial weight matrix is row-standardized (Kim et al., 2003; Steimetz, 2010). The marginal implicit price is then derived as $\beta_i (1-\rho)^{-1}$. Following this method, the coefficients of SLM in this study are transformed. SLM result of M1 demonstrates that every 1% decrease in the distance from a housing to the nearest park increases housing price by 0.044 % ($\beta_i (1-\rho)^{-1} = 0.034*(1 - 0.224)^{-1}$), whereas every 1% decrease in the distance to the nearest square increases housing price by 0.054 % ($0.042*(1 - 0.224)^{-1}$). In addition, every 1% increase in the park area increases housing price by 0.015 % ($0.012*(1 - 0.224)^{-1}$), respectively. These results show that due to the pleasant environment provided by parks and squares, their implicit value have been significantly capitalized into housing price. Thus, the amenity value of park and square is revealed and H1 is tested. Most estimates of SLM and SEM are relatively smaller than OLS estimates, indicating that neglecting the spatial autocorrelation of housing price may overestimate the capitalization of characteristics.

5.2. Effect of square dancing on housing price

As shown in Table 5, SLM improves the model fit of OLS (adjusted R^2 of OLS and SLM are 0.561 and 0.581, respectively). The spatial lag term is 0.348 and is significant at the 5% significance level, indicating that housing prices are positively correlated. Similar to the results of M1, the estimates of most independent variables are significant with expected signs.

According to Small and Steimetz (2012), spillover effects can be divided into two types, which are pecuniary spillovers and technological spillovers, and their distinction is quite clear. The spatial dependency is purely monetary for pecuniary spillovers, while the technological spillovers indicate that the enjoyment of living at a location is also influenced by the value of neighboring locations. These two spillovers can be distinguished by how residents benefit from the spillover effect. If residents simply benefit through higher sale price (or rent),

Table 5
Results of M2.

Variables	OLS (1)		SLM (2)		SEM (3)	
	Coe.	Sig.	Coe.	Sig.	Coe.	Sig.
Constant	10.701***	0.000	7.133***	0.000	10.748***	0.000
Ln Age	−0.117***	0.000	−0.125***	0.000	−0.121***	0.000
Ln West Lake distance	−0.349***	0.000	−0.336***	0.000	−0.356***	0.000
Green condition	0.021*	0.060	0.022**	0.043	0.022*	0.052
Ln Bus route	−0.045*	0.051	−0.038*	0.089	−0.039*	0.098
Ln Subway distance	−0.051***	0.000	−0.045***	0.000	−0.050***	0.000
Nearby university	0.065***	0.001	0.059***	0.002	0.048**	0.016
Educational facilities	0.033***	0.009	0.025**	0.042	0.021*	0.096
Sports facilities	0.038***	0.000	0.037***	0.000	0.041***	0.000
Property management	0.042***	0.000	0.039***	0.000	0.039***	0.000
Ln DRTS	0.075***	0.000	0.077***	0.000	0.066***	0.000
Ln D_{park}	−0.036***	0.008	−0.035***	0.008	−0.034***	0.009
Ln S_{park}	0.012*	0.060	0.010	0.121	0.008	0.206
Ln D_{square}	−0.042***	0.003	−0.032**	0.019	−0.027*	0.083
Ln S_{square}	0.018*	0.062	0.025***	0.008	0.029***	0.005
$Dance_{in\ park}$	−0.050**	0.016	−0.058***	0.004	−0.060***	0.004
$Dance_{in\ square}$	−0.116***	0.000	−0.130***	0.000	−0.146***	0.000
Rho			0.348**	0.018		
Lambda					0.537***	0.003
Adj-R^2	0.561		0.581		0.580	

***, **, and * represent the 1%, 5%, and 10 % significance levels, respectively.

this spillover is pecuniary spillovers. It means that the spillover transfers from future homeowners to current homeowners (or from renters to landlords). If residents also gain pleasure from neighboring higher housing price or rent (maybe the neighbors use some of their capital gains to beautify their houses, which external analysts cannot observe), then this spillover is called technological spillovers. Generally, the technological spillovers provide welfare effects to the market, while the pecuniary spillovers are welfare neutral (Baumol and Oates, 1988). Small and Steimetz (2012) found that technological spillovers need to be transmitted through the spatial multiplier as Kim et al. (2003) and Cohen and Coughlin (2008) indicated. However, a spatial multiplier is not necessary for pecuniary spillovers since the effects are fully measured by the coefficients. This is because the indirect spatial effects enter aggregate household willingness to pay and aggregate rents received by landlords with equal and opposite signs and cancel each other (see details in Small and Steimetz (2012)). Actually, square dancing may cause unwanted nuisance. According to Small and Steimetz (2012), this kind of negative externalities is close to pecuniary spillovers considering that there is no obvious welfare implication or pleasure gained. Thus, the direct effect is sufficient to reflect the pure loss in amenity value that results from square dancing.

SLM result in Table 5 shows that $Dance_{in\ park}$ and $Dance_{in\ square}$ are significant with negative signs (coefficients are −0.058 and −0.130, respectively). It means that square dancing significantly decreases nearby housing price. Housing price drops by 5.8 % when people dance in the nearest park. A larger influence is found in the effect of dancing in squares on housing price. Housing price drops by 13.0 % when people dance in the nearest square. This finding indicates that square dancing has a significant negative effect on housing price, revealing the important role played by human activities in the housing market.

This result is as expected and H2 is tested. The empirical results demonstrate that human activities have a significant influence on housing price. As a typical and important Chinese case, the noise from square dancing bothers nearby residents and then decreases adjacent housing price. In addition, most squares in Hangzhou are spacious and well developed. According to the statistic description, the average area of squares is 24.15 ha, which is more than threefold of the average park area (7.59 ha). Consequently, more people may dance in squares compared with parks. As expected, dancing in squares shows a larger negative effect on housing price compared with dancing in parks.

5.3. Mediating effect of square dancing on the premium of parks and squares

Table 6 presents the results of the interactive models. The four interactive terms ($Dance_{in\ park}$*ln D_{park}, $Dance_{in\ park}$*ln S_{park}, $Dance_{in\ square}$*ln D_{square}, and $Dance_{in\ square}$*ln S_{square}) were added to M2 in sequence to investigate whether square dancing shows a mediating effect on the premium of parks or squares. M7 includes all the interactive terms. The adjusted R^2 of SLM of M3 to M7 are approximately 0.574 to 0.632, which are better than those of OLS. The estimations of M3 to M6 are similar to those of M7, indicating the robustness of the empirical results. Thus, the result of M7, which includes all the interactive terms, is mainly interpreted here.

SLM shows that the spatial lag term is 0.769 at the 1% significance level. The variables of Ln D_{park} and Ln D_{square} are still significant (coefficients equal to −0.046 and −0.040, respectively), indicating that housing price increases by 0.199 % ($\beta_i (1-\rho)^{-1} = 0.046*(1 - 0.769)^{-1}$) and 0.173 % ($0.040*(1 - 0.769)^{-1}$) with every 1% decrease in the distance from a housing to the nearest park and square, respectively. In addition, $Dance_{in\ park}$ and $Dance_{in\ square}$ are significant at the 1% significance level with negative signs, indicating that square dancing decreases nearby housing price.

In particular, the interactive term of $Dance_{in\ park}$ * Ln D_{park} is significant at the 5% significance level in M7 (coefficient = 0.047). Its positive sign is opposite to the sign of Ln D_{park}. As shown in Eq. (3), if a park is the place where people do square dancing ($Dance_{in\ park} = 1$), then the total influence of park distance equals to the sum of the coefficients of ln D_{park} (θ_1) and $Dance_{in\ park}$* ln D_{park} (θ_7). Thus, the overall coefficient of park distance dramatically changes from −0.046 to 0.001 (−0.046 + 0.047) if people dance in the nearest park. This result reveals that square dancing impairs the premium of park proximity to a large extent. The amenity value of parks is almost offset by the negative externalities of square dancing. In addition, the interactive term between $Dance_{in\ square}$ and ln D_{square} is only significant with a positive sign in OLS (coefficient = 0.056). Similarly, square dancing changes the coefficient of square distance from −0.052 to 0.004 (−0.052 + 0.056), indicating that square dancing also impairs the amenity value of square proximity.

These results suggest that the premium of open spaces seems to vanish due to the mediating effect of square dancing, which are plausible and H3 is tested. Living next to parks and squares is supposed to be an amenity that increases property value, and this is what the basic model bears out. However, perspectives totally change after considering human activities. In particular, the premium of park proximity significantly drops and approximates to zero when people dance in the nearest park, which reveals that residents may no longer want to live near such parks. Neglecting the influence of human activities may not be able to obtain an accurate estimation on the value of open spaces. However, no significant mediating effect of square dancing on the premium of square proximity is found in the spatial models, which is slightly unexpected. Consequently, distances to squares and parks are further categorized to investigate the potential heterogeneous mediating effect of square dancing on each distance segment.

5.4. Heterogeneous mediating effect of square dancing on different distance segments of parks and squares

Further findings are provided by classifying the distances to parks and squares into different distance segments (Table 7). The cited segments of 0–200 m, 200 m – 1 km, 1–3 km and 3 km above were used to distinguish different segments of park distance. Meanwhile, 0–800 m, 800 m – 1.5 km, 1.5–3 km and 3 km above were used to distinguish the

Table6
ResultsofM3toM7.

Variables	M3OLS	M3SLM	M3SEM	M4OLS	M4SLM	M4SEM	M5OLS	M5SLM	M5SEM	M6OLS	M6SLM	M6SEM	M7OLS	M7SLM	M7SEM
Constant	10.724***	7.102***	10.791***	10.673***	6.857***	10.757***	10.714***	7.079***	10.739***	10.826***	6.397***	10.849***	10.845***	2.934*	10.841***
Ln Age	−0.131***	−0.139***	−0.137***	−0.112***	−0.119***	−0.119***	−0.126***	−0.134***	−0.129***	−0.133***	−0.143***	−0.138***	−0.121***	−0.121***	−0.122***
Ln West Lake distance	−0.347***	−0.321***	−0.356***	−0.345***	−0.338***	−0.348***	−0.356***	−0.341***	−0.362***	−0.363***	−0.319***	−0.362***	−0.352***	−0.349***	−0.353***
Green condition	0.022**	0.026**	0.023**	0.018	0.019*	0.019*	0.024**	0.025**	0.024**	0.025**	0.029***	0.025**	0.020*	0.020**	0.019*
Ln Bus Route	−0.040*	−0.029	−0.033	−0.042*	−0.038*	−0.039	−0.037*	−0.03	−0.041*	−0.040*	−0.028	−0.034	−0.045**	−0.041**	−0.046**
Ln Subway distance	−0.048***	−0.038***	−0.046***	−0.052***	−0.047***	−0.052***	−0.049***	−0.043***	−0.049***	−0.050***	−0.038***	−0.049***	−0.051***	−0.048***	−0.050***
Nearby university	0.068***	0.059***	0.049***	0.064***	0.059***	0.043**	0.056***	0.052***	0.043**	0.062***	0.049***	0.050***	0.054***	0.057***	0.051***
Educational facilities	0.028**	0.021*	0.015	0.034***	0.028**	0.021*	0.031***	0.023*	0.025**	0.026**	0.020*	0.018	0.022*	0.021*	0.019*
Sports facilities	0.039***	0.036***	0.041***	0.038***	0.037***	0.040***	0.038***	0.036***	0.039***	0.040***	0.036***	0.041***	0.046***	0.046***	0.046***
Property management	0.041***	0.037***	0.038***	0.044***	0.042***	0.041***	0.042***	0.040***	0.041***	0.039***	0.034***	0.037***	0.038***	0.038***	0.038***
Ln DRTS	0.062***	0.061***	0.050***	0.078***	0.082***	0.060***	0.072***	0.074***	0.070***	0.061***	0.057***	0.055***	0.047***	0.052***	0.048***
Ln D_{park}	−0.059***	−0.055***	−0.053***	−0.037***	−0.035***	−0.034***	−0.028**	−0.027**	−0.027**	−0.024*	−0.023*	−0.024*	−0.051***	−0.046**	−0.050***
Ln S_{park}	0.015**	0.012**	0.012**	0.016*	0.012	0.007	0.01	0.008	0.008	0.018***	0.014**	0.014**	0.008	0.003	0.007
Ln D_{square}	−0.040***	−0.034**	−0.027*	−0.042***	−0.029**	−0.028*	−0.078***	−0.060***	−0.042*	−0.036***	−0.030**	−0.032**	−0.052**	−0.040*	−0.039*
Ln S_{square}	0.022**	0.029***	0.032***	0.016*	0.024**	0.027**	0.027***	0.032***	0.038***	−0.002	0.007	0.008	0.003	0.006	0.011
$Dance_{in\ park}$	−0.037*	−0.050**	−0.049**	−0.043*	−0.051**	−0.063***	−0.056***	−0.063***	−0.062***	−0.069***	−0.078***	−0.070***	−0.065***	−0.069***	−0.065***
$Dance_{in\ square}$	−0.111***	−0.120***	−0.140***	−0.119***	−0.135***	−0.145***	−0.141***	−0.145***	−0.155***	−0.239***	−0.232***	−0.230***	−0.315***	−0.319***	−0.297***
$Dance_{in\ park}$ * $\ln D_{park}$	0.052**	0.048**	0.043*										0.052**	0.047**	0.048**
$Dance_{in\ park}$ * $\ln S_{park}$				−0.009	−0.006	0.001							0.015	0.019	0.015
$Dance_{in\ square}$ * $\ln D_{square}$							0.053**	0.039	0.021				0.056**	0.040	0.042
$Dance_{in\ square}$ * $\ln S_{square}$										0.048**	0.044**	0.039*	0.065***	0.067***	0.057***
Rho		0.352***			0.373**			0.355**			0.429***			0.769***	
Lambda			0.567***			0.529***			0.749***			0.379*			0.565**
Adj-R^2	0.601	0.624	0.619	0.553	0.574	0.572	0.588	0.608	0.608	0.602	0.632	0.618	0.587	0.611	0.605

***, **, and * represent the 1%, 5%, and 10 % significance levels, respectively.

Table 7
Results of M8 to M10.

Variables	M8 OLS	M8 SLM	M8 SEM	M9 OLS	M9 SLM	M9 SEM	M10 OLS	M10 SLM	M10 SEM
	Coe.	Coe.	Coe.	Coe.	Coe.	Coe.	Coe.	Coe.	Coe.
Constant	10.448***	8.079***	10.601***	10.590***	8.210***	10.609***	10.458***	7.584***	10.511***
Ln Age	−0.115***	−0.124***	−0.125***	−0.140***	−0.145***	−0.145***	−0.126***	−0.136***	−0.133***
Ln West Lake distance	−0.302***	−0.286***	−0.305***	−0.337***	−0.321***	−0.342***	−0.345***	−0.323***	−0.349***
Green condition	0.025**	0.028***	0.028**	0.017	0.019*	0.018*	0.018*	0.022**	0.021**
Ln Bus route	−0.030	−0.022	−0.028	−0.059***	−0.053***	−0.051**	−0.045**	−0.035*	−0.039*
Ln Subway distance	−0.056***	−0.053***	−0.056***	−0.054***	−0.048***	−0.054***	−0.051***	−0.045***	−0.052***
Nearby university	0.073***	0.067***	0.054***	0.057***	0.053***	0.047***	0.053***	0.044**	0.041**
Educational facilities	0.034***	0.027**	0.021*	0.021*	0.016	0.015	0.020*	0.014	0.016
Sports facilities	0.036***	0.034***	0.037***	0.039***	0.038***	0.040***	0.043***	0.040***	0.042***
Property management	0.043***	0.041***	0.039***	0.041***	0.038***	0.037***	0.041***	0.037***	0.038***
Ln DRTS	0.057***	0.055***	0.049***	0.073***	0.071***	0.063***	0.070***	0.066***	0.063***
Ln D_{park}				−0.020	−0.022*	−0.022*			
Ln S_{park}	0.015**	0.012*	0.012*	0.008	0.005	0.005	0.007	0.003	0.005
Ln D_{square}	−0.033**	−0.030**	−0.016						
Ln S_{square}	0.001	0.005	0.000	0.025***	0.029***	0.034***	0.027***	0.033***	0.036***
$DP_{0–0.2}$	0.242**	0.219**	0.188*				0.246**	0.231**	0.211**
$DP_{0.2–1}$	0.144**	0.114	0.084				0.150**	0.126*	0.116*
$DP_{1–3}$	0.059	0.026	0.005				0.080	0.049	0.041
$Dance_{in\ park} * DP_{0–0.2}$	−0.157**	−0.172**	−0.185**				−0.171**	−0.184**	−0.172**
$Dance_{in\ park} * DP_{0.2–1}$	−0.070***	−0.073***	−0.090***				−0.081***	−0.081***	−0.081***
$Dance_{in\ park} * DP_{1–3}$	0.016	0.009	−0.016				−0.009	−0.012	−0.006
$DS_{0–0.8}$				0.204***	0.191***	0.201***	0.170***	0.157***	0.165***
$DS_{0.8–1.5}$				0.220***	0.200***	0.215***	0.187***	0.165***	0.183***
$DS_{1.5–3}$				0.210***	0.190***	0.205***	0.186***	0.166***	0.184***
$Dance_{in\ square} * DS_{0–0.8}$				−0.078*	−0.086*	−0.103**	−0.091*	−0.097**	−0.107**
$Dance_{in\ square} * DS_{0.8–1.5}$				−0.134***	−0.135***	−0.157***	−0.145***	−0.143***	−0.164***
$Dance_{in\ square} * DS_{1.5–3}$				−0.134***	−0.141***	−0.157***	−0.127***	−0.133***	−0.143***
Rho		0.234*			0.233*			0.284**	
Lambda			0.581***			0.501**			0.454**
Adj-R^2	0.561	0.587	0.587	0.592	0.611	0.610	0.591	0.622	0.618

***, **, and * represent the 1%, 5%, and 10 % significance levels, respectively.

segments of square distance. The regression results show that the adjusted R^2 of all models are between 0.561 and 0.622, which indicate a good explanatory power. In addition, most variables are significant with expected signs. M10 includes all the variables, and the following part mainly interprets the result of SLM in M10 due to its better explanatory power. The variables of $Dance_{in\ park}$ and $Dance_{in\ square}$ are not included in the model due to multicollinearity.

The SLM result of M10 shows that the variables of $DP_{0–0.2}$ and $DP_{0.2–1}$ are positive and significant, while the variable of $DP_{1–3}$ is insignificant. It indicates that the segments of 0–200 m (coefficient = 0.231) and 200 m – 1 km (coefficient = 0.126) benefit from nearby parks, whereas the prices of housing beyond 1 km from the park are not influenced by park proximity. The nearest housing (within 200 m from parks) benefit the most due to the pleasant environment provided. In addition, the interactive terms of $Dance_{in\ park} * DP_{0–0.2}$ and $Dance_{in\ park} * DP_{0.2–1}$ are significant with negative signs (coefficients are −0.184 and −0.081, respectively), while the interactive term between $Dance_{in\ park}$ and $DP_{1–3}$ is not significant. This result shows that a mediating effect of square dancing exists in these two adjacent segments (within 1 km from parks), indicating that H4 is tested. The threshold of this mediating effect (shown in Fig. 3) is 1 km. Generally, if people dance in the park, then the actual premium of park proximity in the 0–200 m and 200 m – 1 km segments decreases from 0.231 to 0.047 (0.231–0.184) and from 0.126 to 0.045 (0.126–0.081), respectively. The closer region is affected more significantly by square dancing compared with farther areas. In this case, square dancing impairs the perceived amenity value of parks and housing next to parks may be not so attractive to residents.

As for squares, SLM result of M10 shows that the coefficients of $DS_{0–0.8}$, $DS_{0.8–1.5}$ and $DS_{1.5–3}$ are 0.157, 0.165, and 0.166, and are all significant at the 1% significance level. This indicates that squares show a significant and positive effect on housing price in the three segments (within 3 km from squares). In particular, all interactive terms between $Dance_{in\ square}$ and $DS_{0–0.8}$, $DS_{0.8–1.5}$ and $DS_{1.5–3}$ are significant with negative signs (coefficients are –0.097, –0.143 and –0.133, respectively), which indicates that square dancing significantly impairs the premium of square proximity. If people dance in the square, then the coefficient of square proximity significantly decreases from 0.157 to 0.060 (0.157–0.097) in the 0–800 m segment, from 0.165 to 0.022 (0.165–0.143) in the 800 m – 1.5 km segment, and from 0.166 to 0.033 (0.166–0.133) in the 1.5–3 km segment. This result reveals that square dancing also shows a significant mediating effect on the premium of square proximity and this mediating effect is heterogeneous across different distance segments. The implicit value of squares decreases because of the potential negative externalities of square dancing.

6. Conclusions

This study uses the hedonic price model and spatial econometric models to investigate an interesting phenomenon in China, that is, the effect of square dancing on housing price and open space. The focus of this study is on the influence of human activities on the housing market, which has rarely been investigated before. The empirical study was conducted in Hangzhou, a city with many well-preserved urban parks and squares in China. The spatial econometric model was used to improve the traditional hedonic price model. The results are of great significance as they provide innovative implications of the externalities of human activities, such as square dancing that involves up to 100 million people worldwide. We present three major findings:

(1) Park proximity, park area, and square proximity have significant added value on nearby housing price. H1 is tested. SLM of M1 shows that every 1% decrease in the distance from a housing unit to the nearest park and square increases housing price by 0.044 % and 0.054 %, respectively. In addition, every 1% increase in the nearest park area increases housing price by 0.015 %.
(2) Square dancing significantly decreases housing price. H2 is tested.
Nearby housing price drops by 5.8 % when people dance in the nearest park and 13.0 % when people dance in the nearest square. This result demonstrates that square dancing shows a profound effect on housing price compared with other characteristics, and a more significant influence is found in the effect of dancing in squares on housing price than the effect of dancing in parks.
(3) Square dancing shows a spatial heterogeneous mediating effect on the premium of parks and squares. H3 and H4 are tested. The premium of park proximity in the 0–200 m and 200 m – 1 km segments from the park decreases from 0.231 to 0.047 and from 0.126 to 0.045, respectively. This mediating effect only exists within 1 km from the park (threshold distance in Fig. 3). Whereas the influence of dancing in square is a bit larger. The premium of living in the 0–800 m, 800 m – 1.5 km, and 1.5–3 km segments from the square decreases from 0.157 to 0.060, from 0.165 to 0.022, and from 0.166 to 0.033, respectively, if people dance in the nearest square. This result indicates that the premium of open spaces seems to vanish due to the negative external effect of square dancing and this mediating effect shows spatial heterogeneity.

This study supplements existing studies by providing empirical evidence that has rarely been explored before. Although many dancers benefit from square dancing, this human activity has a significant negative external effect. This study reveals this interesting phenomenon using the data of the housing market. The results indicate that square dancing has an extensive and negative external effect on housing price and open spaces. This finding informs us that this type of human activity not only disturbs the daily lives of residents but also impairs the value of public facilities (e.g., parks and squares) and residential properties. Although many news reports describe residents′ discontent and complaint on square dancing, the local government in China pays little attention to this phenomenon. In fact, square dancing should not be banned because the elderly can benefit from it. As shown in Fig. 1 in Section 3, as the negative external effect of square dancing is tested, its cost and benefit should be balanced to achieve the optimum at which the public and individuals can benefit from. Consequently, actions should be taken to control the externalities of square dancing and protect the right for dancers in the meantime. First, the government may encourage city managers or the police to regulate the noise and chaos caused by square dancing. As our empirical results show, the mediating effect of dancing in parks exists within a threshold of 1 km from the park because of diminishing noise pollution. Thus, the music volume may be restricted to a reasonable range and the dance time may be limited to a suitable period, which will not prevent nearby residents from having needed rest. In addition, noise buffers can be equipped around existing parks and squares to mitigate the nuisance for nearby residents since the negative externalities associated with square dancing are revealed in this study. Future urban planning and construction may consider developing more greenbelts or other kinds of noise buffers (e.g., pavements and parking lots) around parks and squares to alleviate the potential influence of human activities on open spaces and nearby residents. Also, we can learn experience from the Pigovian tax enacted in many western countries. Pigovian tax is designed to deal with the negative externalities in the market (e.g., environment pollution) and to correct the inefficient and unfair outcome. The government may consider levy a similar tax on those people participating in square dancing or charge a fee to dance in open spaces. The optimal total fee would equal to the difference between marginal social cost and marginal private cost. It might be another option to help achieve the social optimum. Meanwhile, what these dancers really need are particular places for square dancing. The development of public sports venues should be accelerated to ensure the benefits of such a large number of dancers. In this manner, the benefits of dancers and residents can be ensured and their conflicts may disappear. Ultimately, a harmonious society will be achieved and the value of parks, squares, and other open spaces will be improved if the negative externalities of human activities are under control.

This study uses the spatial econometric models considering the spatial autocorrelation of housing prices to improve the traditional hedonic price model. In general, the contributions of this study are twofold: The first contribution is (1) to quantify the negative external effect of square dancing on housing price. The significant externalities of square dancing on the housing market are revealed, which show the profound influence of human activities on housing price. To the best of our knowledge, this study is the first to explore in depth the externalities of square dancing, which is a typical human activity, on the housing market in China. The second contribution is (2) to quantify the mediating effect of square dancing on the value of open spaces. Existing studies mainly focused on the effects of static attributes of open spaces but failed to investigate the mediating effect of human activities on open spaces. Thus, it is difficult for these studies to draw comprehensive and in-depth conclusions on the value of open spaces. This study fills the knowledge gaps in existing studies by providing further evidence on the external effect of square dancing on housing price and the value of open spaces. However, this study also has limitations, which may guide future research. There may be several other nuisances in parks and squares (e.g., noise and crime). These potential nuisances may be corelated with square dancing and other human activities and then integratedly influence nearby residents and the housing market. Due to the difficulty in collecting relevant data of such unobservable phenomenon, the link between square dancing and these potential nuisances was not considered. Although the empirical results and general conclusions of this study will not be influenced, more implications might be offered by studying further on this point. Thus, future studies may try to consider this link and provide more evidence on the underlying mechanism behind the effect of square dancing.

Moreover, the influence of square dancing is complex and worthy of further research. Future studies may also consider to explore the effect of square dancing more deeply by taking into account several characteristics of dancing events, such as the size of dancing troupes, the decibel level of music, and different dancing styles performed. In addition, future studies may consider looking at this problem from a micro perspective. For example, the dancers who benefit from square dancing may not live next to open spaces, while nearby residents suffer from the noise that they cannot prevent. Further considering the distances from dancers′ residents to open spaces may provide an in-depth evidence on the reaction of these two kinds of people. A great deal of preparatory work is required to obtain the data. Then, a more valuable and interesting mechanism behind this influence would be revealed. In this way, a better understanding of square dancing, which is one of the most representative human activities in many Chinese cities, would be obtained.

This study provides local governments with implications to control the negative externalities of square dancing and, finally, protect the benefits of all citizens and improve the value of open spaces and residential properties. The results and implications of this study can be generalized to other Chinese cities or countries where square dancing or other human activities (e.g., night market) are popular. Furthermore, the research framework and theoretical structure of this study can be referred by similar studies that focus on the influence of human activities on the housing market.

CRediT authorship contribution statement

Yue Xiao: Investigation, Formal analysis, Writing - original draft. Eddie C.M. Hui: Conceptualization, Supervision, Funding acquisition. Haizhen Wen: Supervision, Methodology, Writing - review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Acknowledgment

This study was funded by The Hong Kong Polytechnic University's research funding (Project No. G-SB0D) and National Natural Science Foundation of China (NO.71974169).

References

Anselin, L., 1988. Spatial Econometrics: Methods and Models. Kluwer Academic Publishers.
Anselin, L., 2004. Exploring spatial data with GeoDaTM: a workbook. Urbana 51, 61801.
Baumol, W.J., Oates, W.E., 1988. The Theory of Environmental Policy, 2nd edition. Cambridge University Press, Cambridge.
Bayer, P., Keohane, N., Timmins, C., 2009. Migration and hedonic valuation: the case of air quality. J. Environ. Econ. Manage. 58 (1), 1–14.
Boennec, R.L., Salladarré, F., 2017. The impact of air pollution and noise on the real estate market. The case of the 2013 European green capital: Nantes, France. Ecol. Econ. 138, 82–89.
Chasco, C., Gallo, J.L., 2013. The impact of objective and subjective measures of air quality and noise on house prices: a multilevel approach for downtown Madrid. Econ. Geogr. 89 (2), 127–148.
Chasco, C., Gallo, J.L., 2015. Heterogeneity in perceptions of noise and air pollution: a spatial quantile approach on the city of Madrid. Spat. Econ. Anal. 10 (3), 317–343.
Chattopadhyay, S., 1999. Estimating the demand for air quality: new evidence based on the Chicago housing market. Land Econ. 75 (1), 22–38.
Chay, K.Y., Greenstone, M., 2005. Does air quality matter? Evidence from the housing market. J. Polit. Econ. 113 (2), 376–424.
Chen, J., Hao, Q., Yoon, C., Powe, D.N., Willis, D.K., Page, G.B., 2017. Measuring the welfare cost of air pollution in shanghai: evidence from the housing market. J. Environ. Plan. Manag. 1–14.
China Daily, 2018. Asia Weekly (12 Feb. 2018). Square shuffle. http://epaper. chinadailyasia.com/asia-weekly/article-14010.html.
Cho, S.H., Bowker, J.M., Park, W.M., 2006. Measuring the contribution of water and green space amenities to housing values: an application and comparison of spatially weighted hedonic models. J. Agri. Resour. Econ. 31 (3), 485–507.
Cho, S.H., Lambert, D.M., Kim, S.G., Roberts, R.K., Park, W.M., 2011. Relationship between value of open space and distance from housing locations within a community. J. Geogr. Syst. 13 (4), 393–414.
Cohen, J.P., Coughlin, C.C., 2008. Spatial hedonic models of airport noise, proximity, and housing prices. J. Reg. Sci. 48 (5), 859–878.
Conway, D., Li, C.Q., Wolch, J., Kahle, C., Jerrett, M., 2010. A spatial autocorrelation approach for examining the effects of urban greenspace on residential property values. J. Real Estate Financ. Econ. 41 (2), 150–169.
Crompton, J.L., 2005. The impact of parks on property values: empirical evidence from the past two decades in the United States. Manag. Leis. 10 (4), 203–218.
Czembrowski, P., Kronenberg, J., 2016. Hedonic pricing and different urban green space types and sizes: insights into the discussion on valuing ecosystem services. Landsc. Urban Plan. 146, 11–19.
Dekkers, J.E.C., Straaten, J.W.V.D., 2009. Monetary valuation of aircraft noise: a hedonic analysis around Amsterdam airport. Ecol. Econ. 68 (11), 2850–2858.
Diao, M., Qin, Y., Sing, T.F., 2016. Negative externalities of rail noise and housing values: evidence from the cessation of railway operations in Singapore. Real Estate Econ. 44 (4), 878–917.
Du, X., Huang, Z., 2018. Spatial and temporal effects of urban wetlands on housing prices: evidence from Hangzhou, China. Land Use Policy 73, 290–298.
Dubin, R., 2003. Robustness of spatial autocorrelation specifications: some Monte Carlo evidence. J. Reg. Sci. 43 (2), 221–248.
Elhorst, J.P., 2010. Applied spatial econometrics: raising the bar. Spat. Econ. Anal. 5 (1), 1742–1780.
Elhorst, J.P., 2014. Spatial Panel Data Models. Springer, Berlin Heidelberg.
Espey, M., Owusu-Edusei, K., 2001. Neighborhood parks and residential property values in Greenville, South Carolina. J. Agric. Appl. Econ. 33 (3), 487–492.
Franck, M., Eyckmans, J., Jaeger, S.D., Rousseau, S., 2015. Comparing the impact of road noise on property prices in two separated markets. J. Environ. Econ. Policy 4 (1), 30.
Hammer, T.R., Coughlin, R.E., Horn, I.V., E. T, 1974. The effect of a large urban park on real estate value. J. Am. Inst. Plann. 40 (4), 274–277.
Harrison, D., Rubinfeld, D.L., 1978. Hedonic housing prices and the demand for clean air. J. Environ. Econ. Manage. 5 (1), 0–102.
Hendry, D.F., 1995. Dynamic Econometrics. Oxford University Press, Oxford.
Hughes, W.T., Sirmans, C.F., 1992. Traffic externalities and single-family house prices. J. Reg. Sci. 32 (4), 487–500.
Hui, E.C.M., Liang, C., 2016. Spatial spillover effect of urban landscape views on property price. Appl. Geogr. 72, 26–35.
Hui, E.C.M., Chau, C.K., Pun, L., Law, M.Y., 2007. Measuring the neighboring and environmental effects on residential property value: using spatial weighting matrix. Build. Environ. 42 (6), 2333–2343.
Hui, E.C.M., Zhong, J., Yu, K., 2012. The impact of landscape views and storey levels on property prices. Landsc. Urban Plan. 105, 86–93.
Hui, E.C.M., Liang, C., Yip, T.L., 2018. Impact of semi-obnoxious facilities and urban renewal strategy on subdivided units. Appl. Geogr. 91, 144–155.
Irwin, E.G., Roe, B.E., Morrowjones, H., 2004. The effects of farmland, farmland preservation and other neighborhood amenities on proximate housing values: results of a conjoint analysis of housing choice. Land Econ. 80 (1), 55–75.
Jiao, L., Liu, Y., 2010. Geographic Field Model based hedonic valuation of urban open spaces in Wuhan, China. Landsc. Urban Plan. 98 (1), 47–55.
Jim, C.Y., Chen, W.Y., 2006. Impacts of urban environmental elements on residential housing prices in Guangzhou (China). Landsc. Urban Plan. 78 (4), 422–434.
Jim, C.Y., Chen, W.Y., 2010. External effects of neighbourhood parks and landscape elements on high-rise residential value. Land Use Policy 27 (2), 662–670.
Kim, C.W., Phipps, T.T., Anselin, L., 2003. Measuring the benefits of air quality improvement: a spatial hedonic approach. J. Environ. Econ. Manage. 45 (1), 24–39.
Kong, F., Yin, H., Nakagoshi, N., 2007. Using GIS and landscape metrics in the hedonic price modeling of the amenity value of urban green space: a case study in Jinan city, China. Landsc. Urban Plan. 79 (3), 240–252.
Lancaster, K.J., 1966. A New approach to consumer theory. J. Polit. Econ. 74 (2), 132–157.
LeSage, J.P., 1999. The Theory and Practice of Spatial Econometrics. University of Toledo, Toledo, Ohio, pp. 28–33.
LeSage, J.P., Pace, R.K., 2009. Introduction to Spatial Econometrics. CRC Press.
LeSage, J.P., Pace, R.K., 2010. Spatial Econometric Models. Springer, Berlin Heidelberg.
Liang, C., Hui, E.C.M., Leung, Y.T., 2018a. Time on market (TOM): the impact of new residential stamp duty. Physica A 503, 1117–1130.
Liang, X., Liu, Y., Qiu, T., Jing, Y., Fang, F., 2018b. The effects of locational factors on the housing prices of residential communities: the case of Ningbo, China. Habitat Int. 81, 1–11.
Liao, W.C., Wang, X., 2012. Hedonic house prices and spatial quantile regression. J. Hous. Econ. 21 (1), 16–27.
Long, F., Zheng, S., Wang, Y., 2009. Estimation of urban public service value based on the spatial econometric model. Tsinghua Sci. Technol. (Natural Science) 12, 2028–2031.
Lutzenhiser, M., Netusil, N.R., 2001. The effect of open spaces on a home's sale price. Contemp. Econ. Policy 19 (3), 291–298.
Morancho, A.B., 2003. A hedonic valuation of urban green areas. Landsc. Urban Plan. 66 (1), 35–41.

Munneke, H.J., Slawson, V.C., 1999. A housing price model with endogenous externality location: a study of mobile home parks. J. Real Estate Financ. Econ. 19 (2), 113–131.
Mur, J., Angulo, A., 2009. Model selection strategies in a spatial setting: some additional results. Reg. Sci. Urban Econ. 39 (2), 200–213.
Nelson, J.P., 1978. Residential choice, hedonic prices, and the demand for urban air quality. J. Urban Econ. 5 (3), 357–369.
O'Byrne, P.H., Nelson, J.P., Seneca, J.J., 1985. Housing values, census estimates, disequilibrium, and the environmental cost of airport noise: a case study of Atlanta. J. Environ. Econ. Manage. 12 (2), 0–178.
Paelinck, J., Klaassen, L., 1979. Spatial Econometrics. Saxon House, Farnborough.
Panduro, T.E., Veie, K.L., 2013. Classification and valuation of urban green spaces—a hedonic house price valuation. Landsc. Urban Plan. 120 (6), 119–128.
Qu, S., Hu, S., Li, W., Zhang, C., Li, Q., Wang, H., 2020. Temporal variation in the effects of impact factors on residential land prices. Appl. Geogr. 114, 102124.
Rosen, S., 1974. Hedonic prices and implicit Markets: product differentiation in pure competition. Ups. J. Med. Sci. 82 (2), 134–137.
Sander, H.A., Polasky, S., 2009. The value of views and open space: estimates from a hedonic pricing model for Ramsey County, Minnesota, USA. Land Use Policy 26 (3), 837–845.
Shultz, S.D., King, D.A., 2001. The use of census data for hedonic price estimates of openspace amenities and land use. J. Real Estate Financ. Econ. 22 (2–3), 239–252.
Small, K., Steimetz, S., 2012. Spatial hedonics and the willingness to pay for residential amenities. J. Reg. Sci. 52, 635–647.
Steimetz, S., 2010. Spatial multipliers in hedonic analysis: a comment on "spatial hedonic models of airport noise, proximity, and housing prices". J. Reg. Sci. 50, 995–998.
Swoboda, A., Nega, T., Timm, M., 2015. Hedonic analysis over time and space: the case of house prices and traffic noise. J. Reg. Sci. 55 (4), 644–670.
Tajima, K., 2010. New estimates of the demand for urban green space: implications for valuing the environmental benefits of Boston's big dig project. J. Urban Aff. 25 (5), 641–655.
Tian, G., Wei, Y.D., Li, H., 2017. Effects of accessibility and environmental health risk on housing prices: a case of Salt Lake County, Utah. Appl. Geogr. 89, 12–21.
Trojanek, R., Tanas, J., Raslanas, S., Banaitis, A., 2017. The impact of aircraft noise on housing prices in Poznan. Sustainability 9, 2088.
Troy, A., Grove, J.M., 2008. Property values, parks, and crime: a hedonic analysis in Baltimore, MD. Landsc. Urban Plan. 87 (3), 233–245.
Weiss, C.C., Purciel, M., Bader, M., Quinn, J.W., Lovasi, G., Neckerman, K.M., Rundle, A.G., 2011. Reconsidering access: park facilities and neighborhood disamenities in New York City. J. Urban Health 88 (2), 297–310.
Wen, H., Zhang, Y., Zhang, L., 2015. Assessing amenity effects of urban landscapes on housing price in Hangzhou, China. Urban For. Urban Green. 14 (4), 1017–1026.
Wen, H., Jin, Y., Zhang, L., 2017a. Spatial heterogeneity in implicit housing prices: evidence from Hangzhou, China. Int. J. Strateg. Prop. Manag. 21 (3), 15–28.
Wen, H., Xiao, Y., Zhang, L., 2017b. School district, education quality, and housing price: Evidence from a natural experiment in Hangzhou, China. Cities 66, 72–80.
Wen, H., Gui, Z., Tian, C., Xiao, Y., Fang, L., 2018. Subway opening, traffic accessibility, and housing prices: a quantile hedonic analysis in Hangzhou, China. Sustainability 10 (7), 2253–2276.
Wen, H., Xiao, Y., Hui, E.C.M., 2019. Quantile effect of educational facilities on housing price: do homebuyers of higher-priced housing pay more for educational resources? Cities 90 (7), 100–112.

Wilhelmsson, M., 2000. The impact of traffic noise on the values of single-family houses. J. Environ. Plan. Manag. 43 (6), 799–815.
Winke, T., 2017. The impact of aircraft noise on apartment prices: a differences-in-differences hedonic approach for Frankfurt, Germany. J. Econ. Geogr. 17, 1283–1300.
Wu, W., Dong, G., 2014. Valuing the' green' amenities in a spatial context. J. Reg. Sci. 54 (4), 569–585.
Wu, J., Wang, M., Li, W., Peng, J., Huang, L., 2015. Impact of urban green space on residential housing prices: case study in Shenzhen. J. Urban Plan. Dev. 141 (4), 05014023.
Wu, C., Ye, X., Du, Q., Luo, P., 2017a. Spatial effects of accessibility to parks on housing prices in Shenzhen, China. Habitat Int. 63, 45–54.
Wu, W., Dong, G., Zhang, W., 2017b. The puzzling heterogeneity of amenity capitalization effects on land markets. Papers Reg. Sci. 96, 136–153.
Wu, J., Song, Y., Liang, J., Wang, Q., Lin, J., 2018. Impact of mixed land use on housing values in high-density areas: evidence from Beijing. J. Urban Plan. Dev. 144 (1), 1–12 05017019.
Xiao, Y., Hui, E.C.M., Wen, H., 2019. Effects of floor level and landscape proximity on housing price: a hedonic analysis in Hangzhou, China. Habitat Int. 87, 11–26.
Yuan, F., Wu, J., Wei, Y.D., Wang, L., 2018. Policy change, amenity, and spatiotemporal dynamics of housing prices in Nanjing, China. Land Use Policy 75, 225–236.
Zabel, J.E., Kiel, K.A., 2000. Estimating the demand for air quality in four U.S. Cities. Land Econ. 76 (2), 174–194.
Zheng, S., Cao, J., Kahn, M.E., Sun, C., 2014. Real estate valuation and cross-boundary air pollution externalities: evidence from Chinese cities. J. Real Estate Financ. Econ. 48 (3), 398–414.
Zheng, S., Hu, W., Wang, R., 2016. How much is a good school worth in Beijing? Identifying price premium with paired resale and rental data. J. Real Estate Financ. Econ. 53 (2), 184–199.