The Impact of the Crime Rate and Star Schools on House Prices: An Analysis of Spatial Dependence

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Abstract

This paper discusses the relationships among house prices and house characteristics, crime rates, and star schools. The analyzed data were collected from 12 administrative regions in Taipei city. The empirical results show that star schools have a significant positive impact on house prices; violent crime rates have a negative but not significant impact on house prices; and theft-type crime rates have a significant positive impact, contrary to expectations. We infer that the cause for this counter-intuitive finding may be the psychological burden, but may also be related to theft-type crime rates in commercial development areas. The results also reveal that using the spatial error model and the spatial lag model will modify overestimated parameters in the conventional OLS model.

Keywords: house prices, spatial dependence, hedonic price, crime rate, star school

1. Introduction

For the Chinese community there is a traditional sentiment that if "there is land, there is wealth", so real estate is often used as a method of investment and hedging. In addition, individual house prices are also regarded as a symbol of personal and social wealth. For many consumers, in considering real estate as a high-priced value good, factors taken into consideration in buying and selling real estate will also be relatively complex. As for the four needs of people's livelihood, which include "food, clothing, housing, and transportation", housing is typically the most costly. Regarding the selection of houses, along with work or payment conditions, people tend to consider price, quality, residential location, and transportation convenience, as well as many other characteristics.

Location plays a very important role. The advantages of location mean more chances for an increase in value and a better quality of life. If the house is in a better location, the residents can enjoy better social resources, medical resources, green parks and environmental security, namely, a better quality of life. Therefore, a better location means a better public security situation, a better school zone, and better public facilities. The maintenance of public security and law and order is the responsibility of the local government. To measure this performance, crime rate is one of the best forms of data (Ihlanfeldt & Mayock, 2010). With easy access to information, more and more consumers can gather information about the areas surrounding the houses they are going to buy. Therefore, when consumers are considering a purchase, they can take advantage of the information to learn about any crime problem close to the houses they are thinking of buying.

In addition, the quality of the local public schools is one of the major consideration factors when deciding to buy a house. As pointed out by Zahirovic-Herbert and Turnbull (2008), a family with school-aged children selecting a residential location means two investment decisions: first, a housing investment, and second, the human capital investment in the children. If there are school-aged children in the family, parents expect their children to be able to enter first-class universities. To enter a first class university, they have to enter a star senior high school. Entering into a star junior high school can increase the chances of getting into a start senior high school. Therefore, entering into a senior high school with a higher college or university enrollment rate is a major factor of consideration when deciding to buy a house. This means that, when buying these houses, parents often consider living in the star school zone as early as possible, which means house prices in star school zones are higher, more value-preserving and easier to dispose of.

In fact, crime rates and star schools belong to the concept of spatial clustering. In real life, regardless of real estate prices or peoples' consumption, we encounter the two phenomena of spatial clustering and the spatial spillover effect. Namely, areas of high or low house prices will cluster to form a region; areas with high or low consumption levels will also be connected to form a region. Therefore, despite institutional constraints such as an administrative demarcation, space adjacent relationships may significantly affect consumer behavior, as well as the spatial effects of the real estate market. Most previous studies processed multiple samples as independent cases (Basu & Thibodeau, 1998; Anselin, 1999; Can, 1992), overlooking spatial clustering in real estate consumption. Among the hedonic price models applying OLS (ordinary least squares) for estimation, spatial factors are often regarded as a variable characteristic of a homogeneous area. However, in this way, spatial dependence and clustering will be overlooked (Note 1). However, observations in a cluster formation may be affected by the neighboring environment, transportation convenience and by adjacent facilities. Therefore, although the location variable has been implanted within the model, its residuals also suggest the existence of spatial dependence, which means that the assumption of OLS independence cannot be accepted.

The concept of spatial dependence due to the mutual impact of house prices is also known as "spatial autocorrelation". For example, a highly priced house may be surrounded by other highly priced houses, as opposed to a low-priced house. This creates the problem of spatial autocorrelation. The residuals are mutually affected in a dependent and non-homogeneous manner. This paper determines the location of clusters and introduces these spatial factors into the model in order to explain spatial location by using the spatial attributes. Through a geographically weighted regression (GWR) of the spatial econometric model to improve upon possible errors of OLS, this problem of autocorrelation can be solved.

This paper applies the theories and models of spatial econometrics to analyze the level of correlation between crime rates, star schools and house prices through Geoda and ArcGIS 10 GIS, while using the global spatial autocorrelation (Moran's I) method and the local indicators of spatial association (LISA) method to explore whether there is a certain clustering of house prices or if the distribution of house prices will be affected by crime rate and star school differences. Moreover, the conventional OLS regression model, spatial error model, and the spatial lag model are applied when analyzing the impact of spatial factors on house prices so as to develop a spatial analysis model that is more suitable for house prices.

2. Literature Review

The focus of this study is to investigate the impact of crime rates and star school zones on housing prices and to use the spatial panel data model to estimate these parameters. First, with respect to the impact of the crime rate on housing prices, Lynch and Rasmussen (2001) explored this impact by using housing prices in Jacksonville, Florida. As the research findings suggested, the use of an overall crime rate cannot fully present what the specific impact on house prices is. However, the impact on house prices can be presented by using the rates of violent crime and property-type crimes. Gibbons (2004) studied the impact of theft crime rates on house prices in London during the years 1999–2001. As the empirical results suggest, the impact of a purely damage-type crime rate on house prices is limited. However, such types of crimes can increase other types of crime rates and can therefore affect house prices. After classifying various types of crimes, the impact of each type of crime on house prices is limited. Theft-type and violence type crimes, however, have a relatively higher impact on house prices. Skogan (1999) argued that when people live in an area with high priced houses, the local crime rate can increase noticeably and people have to pay extra maintenance costs, which can cause a rise in house prices. In addition, if people live in an area with a low level of clustering, because of this relative lower local clustering density, they can be easy targets for criminals (Gibbons, 2004). Reppetto (1974) and Pope (1980) pointed out in their studies that if people live in an area of low house prices, most of the criminals come from an adjacent area. When compared to an area of high house prices, the probability of a neighbor committing a crime is much higher. Hence, when the criminals attempt to commit a crime, they tend to pick an area of lower house prices as the protection mechanisms will be poorer and thus the chance to succeed will be higher.

As pointed out in Ihlanfeldt and Mayock (2010)'s study, compared with violent-type crime, the impact of theft-type crime on house prices is relatively low, mainly because violent-type crime has a more considerable psychological impact on victims while the impact of theft-type crime is lower. Therefore, people are willing to pay a certain amount of maintenance costs in order to considerably reduce violent-type crime and theft-type crime. The fact that the general public is willing to pay these extra expenditures is regarded as one of the determining factors of house prices.

Secondly, in reviewing the impact of star school zones on house prices, a school's level of education can have an effect on consumers, and this is therefore a characteristic of house prices. In an ideal experimental design, if all

the characteristics of the experimental group and the control group are the same except for the educational characteristic variable, differences in house prices can fully represent the price of the educational facilities (Bao & Sweeney, 2008). According to general common sense, as well as theories, the quality of adjacent schools is an important location factor (Jud & Watts, 1981). However, as real estate will be highly priced, the chances for a purchase or for turnover are limited in the one person's lifetime. As a result, homebuyers are relatively careful when making purchase decisions. If the homebuyer is a parent of school-aged children, the neighboring "quality school" for the children will be one of the considerations when purchasing a house.

According to the empirical results in Charlotte, North Carolina achieved by Jud and Watts (1981), an increase in academic achievement by one unit for students in a neighboring school will cause an average house price increase of 5.2% ~ 6.2%. Although the empirical regions and data of many researchers are different and the time ranges are not the same, all empirical results are similar. This suggests that school quality can significantly affect the price level of houses, Haurin and Brasington (1996) selected 29 variables (4 variables representing schools) and applied the hedonic price model for the housing market, confirming that the quality of schools in Ohio (in the United States) has a considerable impact on house prices, confirming that the distance from downtown, and the comfortableness (community crime rate, cultural arts, amusement) also have a considerable impact on house prices.

Barrow and Cecilia (2004), using the District of Columbia (again, in the United States) as an empirical research region, argued that school quality is one of the major considerations when selecting a residence. Parents with a higher level of income are willing to pay higher prices in exchange for their children having the opportunity to study in a high quality school (an amount of 3,300 USD extra in exchange for an increase of 100 points in SAT (Standard Aptitude Test) 8 achievement scores). Moreover, Zahirovic-Herbert and Turnbull (2008) explained that, in addition to selling for higher prices, houses with good quality schools in the surrounding area will be for sale for shorter periods of time, and this is therefore beneficial in terms of liquidity.

Brasington (1999) found that public school quality has a considerable impact on adjacent house prices. Student test scores, student attendance, the cost of each student, the student/teacher ratio, and teachers' salaries were all used as characteristic variables of teaching investment. They were found to have a positive impact on house prices. Student graduation rates, teaching experience, and teacher qualifications, on the other hand, have no significant impact on house prices. Clark and Herrin (2000) analyzed the 1990–1994 sample data of Fresno, California, after controlling structure and neighboring characteristic variables, and found that the number and quality of public schools are more important than crime rates and environmental factors for local residents. This conclusion is consistent with the results of a survey by the California public education partnership. Gibbons and Machin (2003) found that British families are more concerned with the educational status of neighbors when selecting houses. Families with more children are willing to pay more. An increase in the number residents of the community by 1% will cause the average house prices to increase by 0.24%.

Conventional models ignore an important fact of real estate prices: due to the proximity of space, there are mutual interactions or price spatial spillover effects in house prices. Dubin (1988) compared the prediction of ex-samples by using OLS and geographic statistics technology, finding that the geographic statistical method using neighborhood characteristics is superior to the OLS regression method. Even though the OLS regression method can process the same issues, the estimation of house prices using an OLS regression may ignore the absolute impact of neighboring house prices, namely, the existence of the a spatial spillover effect. This is like how a real estate broker should consider the prices of surrounding real estate as a reference when considering the real estate under evaluation. Therefore, in the case of the spatial spillover effect of real estate prices, the conventional OLS model's error terms are significantly spatially correlated.

Before the wide application of spatial panel data economics, people often used cross-sectional data, time series data and tracking data for econometric analyses. These conventional analysis methods often used the Gauss-Markov theorem as the premise of assumption. Under the condition of confirmed explanatory variables and estimation parameters, the explained variables and random error terms are distributed in the same pattern, and they support the assumption of normal distribution, and uniform distribution, with covariance being zero. However, such an assumption ignores the various correlations between location and economic and social variables. Therefore, using the conventional OLS estimation method based on the classical assumption when processing spatial data can often result in bias (Cliff & Ord, 1981; Anselin, 1988; Haining, 2003). Dubin, Pace, and Thibodeau (1999) compared the OLS and four different spatial statistic methods, finding that most of the spatial statistical methods perform better than OLS does.

3. Empirical Model Settings and Variable Descriptions

The geographically weighted regression is an innovative analysis method applied to spatial statistics in recent years, particularly to the analysis of local real estate prices. Gao and Asami (2005) discussed the impact of spatial characteristics on house prices by using GWR to measure spatial dependence and spatial heterogeneity in house and land prices and to explain the land price time-space distribution, in an attempt to improve upon the conventional static model. Using the Setagaya Ward in Tokyo, Japan, as an example, they compared the hedonic price model and GWR in terms of interpretative power, finding that GWR has more interpretative power and can better explain the impact of the selected attributes on land and house prices. The study also further distinguishes between the degree and range of impact for variables of lot or area. In recent years, thanks to the technological integration of geographically weighted regression analysis programs and geographic information systems (GIS) software, the studies on the use of GIS software in the geographically weighted regression analysis of all fields are apparently on the rise.

The spatial econometric models can be divided into two main types: the spatial lag model and the spatial error model. Many scholars have found that hedonic price models considering spatial autocorrelation and spatial heterogeneity actually improved estimation results (Cliff & Ord, 1981; Anselin, 1988; Haining, 2003). Chalermpong and Wattana (2010) summarized the impact of housing data's spatial characteristics on the conventional OLS hedonic price model as follows: (1) the spatial econometric model actually improved the fitness of the model; (2) in the conventional OLS method, the estimation coefficient will be overestimated, since the spatial hedonic price method coefficient is lower than that of the conventional OLS method to a certain degree; (3) after controlling for spatial autocorrelation, the significance levels of some variables may change.

This paper applies the OLS regression method to the estimation of house attribute variable's effects on house prices and considers the impact of relevant location variables on house prices. Independent variables include house attribute variables (e.g., area, house age (AGE), house age squared (AGES), number of rooms (ROOM), number of living rooms (LIVROOM), number of bathrooms (BATH), total number of buildings (BUILD), residential floors (DFLOOR), parking spaces (PARK)), location variables (CITYCEN), the year of sale (YEAR09, YEAR10), number of police personnel (POLICE), violence-type crime rate (VIOLENCE), theft-type crime rate (LARCENER) and star schools (STAR3SCHOOL). The model setting is as shown in Eq. (1):

$$\ln P = \alpha_0 + \alpha_1 AREA + \alpha_2 AGE + \alpha_3 AGES + \alpha_4 ROOM + \alpha_5 LIVROOM + \alpha_6 BATH + \alpha_7 BUILD$$
$$+ \alpha_8 DFLOOR + \alpha_9 CITYCEN + \alpha_{10} PARK + \alpha_{11} YEAR09 + \alpha_{12} YEAR10 + \alpha_{13} POLICE + \alpha_{14} LARCENER \quad (1)$$
$$+ \alpha_{15} VIOLENCE + \alpha_{16} STARSCHOOL + \varepsilon$$

where, α_0 is the intercept term, $\alpha_1, ..., \alpha_{16}$, represents the regression coefficient; ε represents the error terms in the normal distribution, the average number is 0, and the variance is σ^2.

Secondly, this paper constructs a spatial lag model. This model's explanatory variables include a dependent variable of spatial "lag" that prevents any similar patterns or random patterns of error terms within the space. The concept of spatial "lag" is similar to a time series model, and the lag effect is produced by the impact of the previous period on the later period. The spatial lag model is commonly applied when "a certain activity in a certain place affects an activity in the neighboring area at the same time and vice versa" and its setting is as shown in Eq. (2):

$$\ln P = \alpha_0 + \rho w(\ln P) + \alpha_1 AREA + \alpha_2 AGE + \alpha_3 AGES + \alpha_4 ROOM + \alpha_5 LIVROOM + \alpha_6 BATH$$
$$+ \alpha_7 BUILD + \alpha_8 DFLOOR + \alpha_9 CITYCEN + \alpha_{10} PARK + \alpha_{11} YEAR09 + \alpha_{12} YEAR10 + \alpha_{13} POLICE \quad (2)$$
$$+ \alpha_{14} LARCENER + \alpha_{15} VIOLENCE + \alpha_{16} STARSCHOOL + \varepsilon$$

where $w(\ln P)$ represents the explained variable multiplied by the spatially neighboring matrix, ρ represents the explained variable's spatial lag coefficient, and ε represents the error term.

In the two equations above, the difference between the spatial lag regression model and the general OLS regression model is the multiplication of the explained variable with the spatially neighboring matrix as one of the explanatory variables. By testing to see whether the explained variable's spatial lag coefficient ρ is significantly different from 0, we can see if the spatial lag model actually has any spatial relation with a neighboring area.

Third, this paper constructs the spatial error model. When spatial dependence is found in an error term, the error term will no longer be white noise but will have spatial autocorrelation. The spatial error model is applicable to

modifications due to the existence of spatial autocorrelation. The interference factors are considered in the error term so as to set the spatial autocorrelation of the model in the error term as shown in Eq. (3) and Eq. (4):

$$\ln P = \alpha_0 + \alpha_1 AREA + \alpha_2 AGE + \alpha_3 AGES + \alpha_4 ROOM + \alpha_5 LIVROOM + \alpha_6 BATH + \alpha_7 BUILD$$
$$+ \alpha_8 DFLOOR + \alpha_9 CITYCEN + \alpha_{10} PARK + \alpha_{11} YEAR09 + \alpha_{12} YEAR10 + \alpha_{13} POLICE \qquad (3)$$
$$+ \alpha_{14} LARCENER + \alpha_{15} VIOLENCE + \alpha_{16} STARSCHOOL + \varepsilon$$

$$\varepsilon = \lambda w \varepsilon + \xi, \quad \xi \sim N(0, \sigma^2) \qquad (4)$$

The spatial error model adds the error term of the regression model to the multiplication of the error term with the neighboring matrix in the weighted space. If the spatial error coefficient λ is significantly different from 0 (namely, if $\lambda \neq 0$), then the spatial error regression model actually has interference factors that cause spatial autocorrelation.

As for estimation using the spatial econometric model, if the least squares method is used, the estimated value of the coefficient will be biased or invalid. Therefore, this paper uses the maximum likelihood estimator (MLE) for estimation.

3.1 Variable Settings

For this paper we selected independent variables according to the hedonic price theory. The variable settings and instructions are as shown in Table 1. The dependent variable of house prices is the natural logarithm of a continuous variable. Variables including area (AREA), house age (AGE), house age squared (AGES), number of rooms (ROOM), number of living rooms (LIVROOM), and number of bathrooms (BATH) are all variables of continuity. The coefficient signs of area, number of rooms, number of living rooms, and number of bathrooms are expected to be positive and the coefficient sign of house age is expected to be negative, while the variable of house age squared is expected to be positive. The total number of buildings (BUILD) and residential floors (DFLOOR) are set as the dummy variables. As for the total number of buildings, that variable is set as 0 in the case of an apartment located on the 1st through 5th floor of a building and as 1 in the case of an apartment located on the 6th floor or above. This means that the higher the total number of buildings, the better the view and the higher the construction cost. Therefore, the prices of houses above the 5th floor will be higher and thus the coefficient sign is expected to be positive. As for the residential floor (DFLOOR), this stands for the floor of the interviewee, and is set as 1 if the interviewee lives in the first floor, while otherwise it is 0. A first floor house can generally be used as a store; therefore, the price is usually higher, which means the coefficient sign is expected to be positive. The parking space (PARK) is set as a dummy variable. It will be 1 if the house has the parking space, otherwise, it will be 0. The coefficient sign is expected to be positive.

Regarding location variables, according to Lee, Chang, and Hua (2006), taking into consideration transportation accessibility and living functions, Taipei City is divided into: Taipei City development area (namely, the downtown area), including Zhongzheng District, Da'an District, Xinyi District, Zhongshan District, Shilin District, and Songshan District. The Taipei suburbs include Nangang District, Wenshan District, Datong District, Wanhua District, Beitou District, Jingmei, and Neihu District. If the house is located in the downtown area, the variable CITYCEN is set as 1, otherwise, it is set as 0, and the coefficient sign is expected to be positive.

Regarding year of sale, there are three years included in this study, which are: 2008, 2009 and 2010, with 2008 being used as the reference benchmark. This paper sets two dummy variables. If the house was sold in 2009, the variable YEAR09 is set as 1, otherwise, it is set as 0. The houses sold in 2009 were affected by transportation facilities (MRT Wenhu Line) and policy changes (encouragement of mainland investment), and were thus higher than in 2008, both in terms of quantity and price. The coefficient sign is therefore expected to be positive. If the house was sold in 2010, the variable YEAR10 is set as 1, otherwise it is set as 0. The transactions in 2010 were starting to get rid of the impact of the financial tsunami and were gradually taking on the situation of a better economy. Coupled with more sales and the signing of the ECFA (Economic Cooperation Framework Agreement), the sales volume or prices in 2010 were higher than those in 2008. Therefore, the coefficient sign is expected to be positive.

The variable of the number of police personnel (POLICE) is a continuity variable representing the total number of police officers in each branch for each administrative region during each year. The coefficient sign is expected to be positive. The variable of the violence-type crime rate (VIOLENCE) is a variable of continuity. Violent-type crimes include robbery, theft, murder, kidnapping, and forced sexual intercourse (rape and gang rape), and the coefficient sign is expected to be negative. The theft-type crime rate (LARCENER) is a variable of

continuity, theft-type crimes include general burglary, major theft, motor vehicle theft, and the coefficient sign is expected to be negative.

Star school (STARSCHOOL) is a variable of continuity, representing the number of star schools in each administrative region, and the coefficient sign is expected to be positive. The common characteristics of these star schools (high quality schools) are a high enrollment rate, high achievement and a high entrance threshold. However, there is no objective standard for the academic achievement of students. Moreover, due to the difficulty in obtaining enrollment data, this paper is unable to determine school quality by achievement, race and other factors like foreign studies; instead, the entrance threshold is used to determine the quality of the school. For this, the new enrollment "full school" indicator published by the Department of Education of the Taipei City Government is used to determine the quality of schools.

Table 1. Variable settings and illustrations

Variable Description	Variable Definition and Illustration	Expected sign
lnP	The natural logarithm of house prices, calculated by taking the natural logarithm of the house part prices (including parking space) (original house price/ unit: 10,000 NTD)	
AREA	House area, the area of a house as registered with land authorities (including major construction, additions, public facilities, parking spaces (covered regardless of whether it is an independent parking space or not).	+
AGE	House age, referring to the period from the completion of the house or the registration of the house to 2010.	--
AGES	According to previous studies, house age depreciation is not a rigid linear model, and the initial period depreciation rate is greater than that during the late stage. If the house age variable is used in the regression model, we can only observe linear changes in house age. Therefore, a hedonic price model will incorporate the variable of house age squared to observe any non-linear changes in depreciation. The expected sign of the house age squared variable is positive.	+
ROOM	Number of rooms, representing the number of rooms in the house.	+
LIVROOM	Number of living rooms, representing the number of living rooms in the house.	+
BATH	Number of bathrooms, representing the number of bathroom facilities in the house.	+
BUILD	Total number of buildings. This is set as a dummy variable, in the case of a building with 1~5 floors, it is set as 0, in the case of a 6 floor building and above, it is set as 1.	+
DFLOOR	Residential floors. This is set as a dummy variable, representing the registered number of floors in the house. In the case of one floor, it is set as 1, otherwise, it is set as 0.	+
PARK	Parking space, representing the inclusion of a parking space or not in the house. It is set as 1 if there is parking space; otherwise, it is set as 0.	+
CITYCEN	Location variable is represented by a dummy variable. The Taipei downtown area includes Zhongzheng District, Da'an District, Xinyi District, Zhongshan District, Shilin District, and Songshan District, and it is set as 1, otherwise it is set as 0.	+
YEAR09	Regarding the year of sale, the three years are 2008, 2009 and 2010, with 2008 as the reference benchmark. This paper sets	+

	two dummy variables. If the house was sold in 2009, the variable of YEAR09 is set as 1, otherwise, it is set as 0.	
YEAR10	If the house was sold in 2010, the variable of YEAR10 is set as 1; otherwise it is set as 0.	+
POLICE	The number of police officers This is a variable of continuity. This paper uses the total number of police officers of each branch in each administrative region during each year.	+
VIOLENCE	The violent-type crime rate is a variable of continuity. Violent-type crimes include robbery, theft, murder, kidnapping, and forced sexual intercourse (rape and gang rape). In this study, the violent-type crime rate refers to the crime rate during each month in each administrative region. (cases/100,000 people)	--
LARCENER	The theft-type crime rate (LARCENER) is a variable of continuity; theft-type crimes include general burglary, major theft, and motor vehicle theft. In this study, the theft-type crime rate refers to the crime rate during each month in each administrative region. (cases/100000 people)	--
STARSCHOOL	The number of star schools (STARSCHOOL) is a variable of continuity. The common characteristics of star schools (high quality schools) are a high enrollment rate, high achievement and a high entrance threshold. This paper uses the entrance threshold to determine the quality of the school, namely the number of star schools with full enrollment in each administrative region. More star schools may cause an increase in house prices.	+

4. Data Source and Sample Statistics Description

4.1 Data Source Description

As for the research data for this study, this paper uses original data from 2008 to 2010 from the "Taiwan Real Estate Trading Center". The Taiwan Real Estate Trading Center was founded in 2005 as a trading information inquiry service. The data are collected from well-known chain housing agencies, including Xinyi housing, Pacific housing, 21st Century, CT-housing, hbhousing, arch-world housing, Good-morning housing, ERA real estate, Ever Spring real estate, and CM housing; in other words mainly data from transactions with performance guarantees. The information includes the transaction price, the building floor area, the house age, house types, the number of floors and other house attributes. With Taipei City as the subject of analysis, this study collected a total of 6600 samples from apartment houses in 12 administrative regions of Taipei City.

Due to the great characteristic differences in real estate, the price differences will also be great. Therefore, the data of each item may contain many outliers. To avoid the impact of these outliers on statistical computation and inference results. This paper first eliminates the top 5% and bottom 5% price samples from various administrative regions and deletes the samples with outliers as well. After this, there are 5740 remaining samples.

The geographically weighted regression (GWR) analysis underlines the conceptual basis of "space" and "distance". For any subsequent spatial construction using a geographically weighted regression model, GIS technology has to be used for assistance in constructing house transaction information on spatial locations. Because of this, the Arc GIS 10 version software is used to construct a spatial attribute database and to connect the spatial location data and the sample attribute data in order to construct a spatial analysis database of house transaction prices. According to the transaction data and the administrative region diagram of Taipei City, as well as the address information, this paper establishes sample points for the spatial data of house transactions in the Taipei City administrative region map by using Google maps and the Hinet mapping technological system. After establishing the spatial database of transaction data for each house in the research range, the Arc GIS 10 version software of the GIS system is used to overlap any locations of transaction data and relevant diagrams so as to measure the distances of these variables and generate distance values for classifying house prices before determining the Moran's I and LISA distribution accordingly.

4.2 Sample Statistics Description

As shown in Table 2, the transaction price (P), on average, is NTD 12,504.7 thousand, while the standard deviation is 6,696.1 thousand. Area (AREA), on average, is 31.91 Ping (1 ping equals 35.58 sq. ft.) and the standard deviation is 12.83. The house age (AGE), on average, is 24.37 years, with a standard deviation of 10.73. The number of rooms (ROOM), on average, is 2.44 rooms, with a standard deviation of 0.87. The number of living rooms (LIVROOM), on average, is 0.88 rooms. The number of bathrooms (BATH), on average, is 1.976. Interviewees with houses on the first floor accounted for (DFLOOR) 12.4% of the total, and interviewees living in houses on other floors accounted for 87.6%. Houses with the total number of buildings (BUILD) above 6 accounted for 33.9%, while houses with the total number of buildings from 1 to 5 accounted for 66.1%. Houses with a parking space (PARK) accounted for 15.8%. Houses in the downtown area (CITYCEN) accounted for 58%, houses in the Taipei suburbs (CITYSUB) accounted for 42%. Houses sold in 2008 (YEAR08) accounted for 22.5% of the total, houses sold in 2009 (YEAR09) accounted for 41.8% of the total, while houses sold in 2010 (YEAR10) accounted for 5.7%. The average number of police personnel (POLICE) is 360.12, suggesting the average number of police officers in each administrative region of the Taipei City is 360.12 people, while the standard deviation is 92.31. The violent-type crime rate (VIOLENCE), on average, is 22.12, indicating that about 22.12 violent-type crimes were committed for every 100,000 people, and the standard deviation is 12.14. The theft-type crime rate (LARCENER), on average, is 622.74, suggesting that about 622.74 theft-type crimes were committed for every 100,000 people, while the standard deviation is 242.53. On average, there are 2.08 star schools (STARSCHOOL) in each administrative region.

Table 2. Descriptive statistics (N= 5740)

	Mean value	Standard deviation	Minimum value	Maximum value
P	1250.47	669.61	325.02	3849.92
AREA	31.91	12.83	5.93	137.22
AGE	24.37	10.73	0.10	52.60
AGES	709.31	473.86	0.01	2766.76
BUILD	0.33	0.47	0	1
DFLOOR	0.12	0.32	0	1
ROOM	2.44	0.87	1	5
LIVROOM	0.88	0.41	0	2
BATH	1.34	0.28	1	3
PARK	0.15	0.35	0	1
CITYCEN	0.58	0.49	0	1
YEAR08	0.23	0.77	0	1
YEAR09	0.41	0.49	0	1
YEAR10	0.36	0.48	0	1
POLICE	360.12	92.31	178	518
LARCENER	622.74	242.53	332.43	1442.64
VIOLENCE	22.12	12.14	7.81	51.21
STARSCHOOL	2.08	1.26	0	4

4.3 Spatial Autocorrelation Test

4.3.1 Global Autocorrelation Analysis

Before conducting any empirical analysis, it is necessary to know whether there is any spatial clustering of house prices. In the field of spatial econometric data, a global spatial autocorrelation Moran's I value can be used to test the spatial correlation level of the research range. The value of Moran's I is between 1 and -1. Applications of Moran's I have been very extensive. Interested readers may refer to the introduction by Cliff and Ord (1981). According to our calculation, Moran's I is 0.1752, reaching a 1% significance level. This suggests that house prices in Taipei City have a positive spatial correlation and have attributes that are similar to neighboring areas with clustering phenomena.

4.3.2 Local Spatial Autocorrelation

As opposed to the global spatial autocorrelation, local spatial autocorrelation (LISA) measures the spatial correlation level in the measurement range; more importantly, it can find any spatial hot spots. This paper applies the LISA method proposed by Anselin (1995) for the observation of a LISA spatial distribution of house prices in Taipei City and the results are as shown in Figure 1. When the LISA analysis results are used in conjunction with the Geoda module of the GIS system, the results can be specifically presented in a house transaction points diagram of the research range. According to the various definitions of LISA values of H-H, L-H, L-L and H-L (as shown in Table 3), coupled with the actual development of the research range, this paper further determines whether there is any spatial clustering of house prices.

Table 3. LISA value descriptions

LISA	Type	Correlation	Clustering	Clustered Attributes
First Quartile	H-H	Positive spatial correlation	Clustering of the same priced	The high-priced is surrounded by the high-priced
Second Quartile	L-H	Negative spatial correlation	Clustering of the differently priced	The low-priced is surrounded by the high-priced
Third Quartile	L-L	Positive spatial correlation	Clustering of the same priced	The low-priced is surrounded by the low-priced
Fourth Quartile	H-L	Negative spatial correlation	Clustering of the differently priced	The high-priced is surrounded by the low-priced

Figure 1 is the house prices LISA spatial distribution. Most of the H-H areas are located in Zhongshan District, Zhongzheng District, Da'an District, Songshan District, and Xinyi District, suggesting that high house prices in these five administrative regions are surrounded by other high house prices. The L-L areas include five administrative regions including Beitou District, Datong District, Wanhua District, Wenshan District, and Neihu District, indicating low house prices of the five administrative regions are surrounded by other low house prices. The L-H area is Nangang District, suggesting that low house prices in Nangang District are surrounded by other houses with high prices.
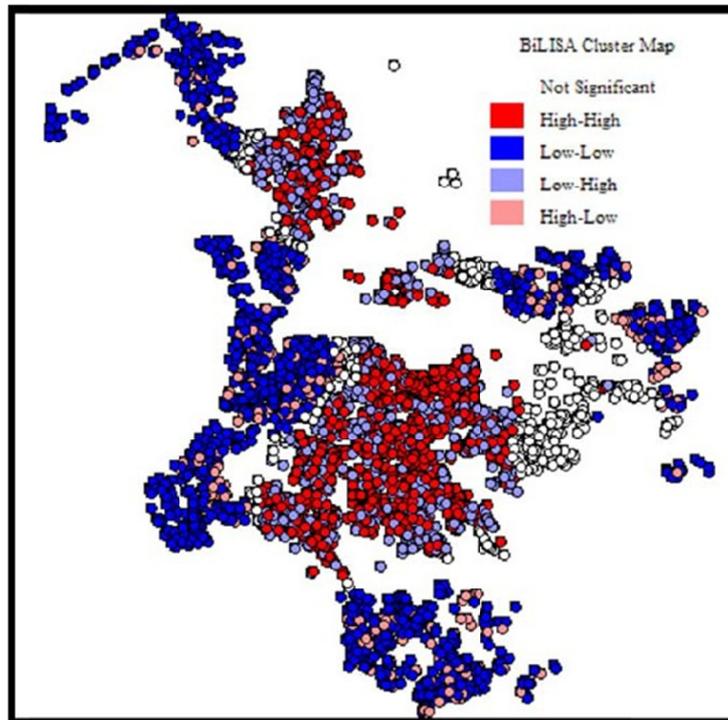
Figure 1. House prices LISA distribution diagram

5. Empirical Results and Analysis

This paper used the VIF (variances inflation factors) value to determine whether there was any serious linearity between independent variables, and found that the VIF values were all below 10. According to the suggestion of Neter, Wasserman, and Kutner (1990), if the VIF value is below 10, it means there is no serious collinearity between independent variables. Second, the OLS was used to test 2008~2010 spatial heterogeneity values in terms of geographic spatial correlation, namely, the spatial dependence level. As shown in Table 4, Moran's I is 0.114 and reaches a significance level (Note 2), indicating that neighboring house prices are positively auto-correlated. Namely, Taipei City's house price spatial distribution is not fully random but consists in spatial clustering of similar values. A spatial econometric model is therefore used for testing. The LM-lag and LM-error are, respectively, 2395.242 and 12638.262, both of which reach a 5% significance level, and Robust LM-lag and Robust LM-error are 409.736 and 10625.757, both of which reach a 5% significance level. As mentioned above, the model rejects the null hypothesis, and the residuals have heterogeneous differences. Therefore, this paper further compares the estimation results of the spatial lag model and the spatial error model. The Koenker-Bassett test statistics is 903.663, reaching a 5% significance level, thus rejecting the null hypothesis. This indicates that these house prices have spatial heterogeneity.

Table 4. Spatial dependence test table (OLS)

Test	MI/DF	Z(I) value
Moran's I	0.114	131.563 **
LM-lag	1	2395.242 **
LM-error	1	12638.262 **
Robust LM-lag	1	409.736 **
Robust LM-error	1	10652.757 **
Koenker-Bassett test	15	903.663 **

Note: MI/DF are Moran' s I value and freedom of degree respectively.

** and * that the coefficient is significantly different from 0 at the 5% and 10% significance levels respectively.

Table 5 illustrates the estimation results by using a conventional OLS model, a spatial lag model, and a spatial error model. The empirical model results of these three models are shown below. Although Table 4 shows that OLS has a spatial dependence and heterogeneity problem, this cannot be used as the only indicator. Therefore, this paper further conducts a Breusch-Pagan test of the three models so as to confirm whether the residuals of the three models are heterogeneous. The coefficients of the three models are 2170.13, 3040.29 and 3275.41, respectively, all of which have reached a 5% significance level, suggesting that the residuals of the three models are heterogeneous. The R^2 values of the three models are 71.57%, 76.57% and 76.99% respectively, and the explanatory power of the spatial error model is the highest. As for AIC (Akaike Information Criterion) and SC (Schwarz Criterion) values, the smaller the coefficient, the better the model fitness. The values are 1354.40, 1182.66, 427.89 and 1460.88, 1069.53, 533.89 respectively. The fitness of the spatial error model is better. Log likelihood test values are -661.19, -608.33 and -197.70 respectively, all of which have reached a 5% significance level. This indicates that, compared with the OLS model, the problem of spatial dependence can be apparently improved in the spatial lag model and the spatial error model. When the Robust LM-lag and the Robust LM-error are both significant, the likelihood ratio values of the spatial lag model and the spatial error model are used to determine the model with the best fit. The Likelihood ratio values of both models are 2539.06 and 926.99, respectively, and both reach a 5% significance level. Hence, when using the Likelihood ratio value to determine model fitness, the smaller the value the better, which means the spatial error model is the best model in terms of fitness. According to the above analysis results, the spatial error model is superior to the spatial lag model, which, in its turn, is superior to the conventional OLS regression model. Hence, in the following analysis and elaborations, the estimation results of the spatial error models will be used as illustration.

Regarding house-related attributes, the estimation coefficients are mostly above the 5% significance level. The area coefficient of estimation is 0.022, which reaches a 5% significance level, indicating that each increase in area by 1 Ping can increase the house price by 2.2%. House age coefficient is -0.012, which reaches a 5% significance level, suggesting each increase in house age by one year can result in a decrease in house price by 1.2%. The square coefficient is 0.001, which reaches a 5% significance level, suggesting a higher house age can result in lower house prices. However, the amplitude of decrease tends to become smaller and smaller. The coefficient of the total number of buildings is 0.080, which reaches a 5% significance level, suggesting that the price of houses above the 6th floor is higher than the prices of houses on the first to the fifth floor by 8%. The floor coefficient is 0.089, which reaches a 5% significance level, indicating that the first floor is higher than other floors by 8.9% in terms of price. The number of rooms' coefficient of estimation is 0.072, which reaches a 5% significance level, indicating that house prices will increase by 7.2% for each increase of one room. The number of living rooms coefficient of estimation is 0.117, which reaches a 5% significance level, indicating that house prices will increase by 11.7% for each additional living room. The number of bathrooms' coefficient of estimation is 0.029, which reaches a 5% significance level, indicating house prices will increase 2.9% for each additional bathroom. The parking space coefficient of estimation is -0.028, which reaches a 5% significance level, indicating that house prices with or without a parking space are not significantly different. The downtown area's coefficient of estimation is 0.067, which reaches a 5% significance level, indicating the house prices in a downtown area are higher than those in the suburbs by 6.7%. The estimation coefficients of sales in 2009 and 2010 are 0.037 and 0.197, respectively, and reach a 5% significance level, indicating that house prices in 2009 and 2010 are higher than those in 2008 by 3.7% and 19.7%, respectively.

As for the house spatial attributes, the coefficient of the number of police officers is 0.001, which reaches a 5% significance level, indicating that house prices will increase by 0.1% with every additional police officer. When the number of police personnel increases, people expect local security to be better maintained, and therefore house prices will increase. These conclusions are consistent with Gibbons (2004). People are willing to pay higher prices to purchase houses if there are more police officers to safeguard local law and order.

The violent-type crime rate's coefficient of estimation is -0.001, indicating that house prices will decrease by 0.1% when violent type crime rate increases, although it does not reach a 10% significance level. The theft-type crime rate coefficient of estimation is 0.001, which reaches a 5% significance level, suggesting that house prices will increase by 0.1% when the theft-type crime rate increases. The coefficient of estimation of the theft-type crime rate is contrary to expectations. In general, since people will consider the local residential environment before purchase, if the local crime rate increases, house prices should tend to decline. However, according to our empirical results, theft-type crimes work contrary to expectations. This is consistent with Ihlanfeldt and Mayock (2010). As illustrated in their study, theft-type crime is not directed physically against people, and the psychological pressure of such a type of crime is not great. In addition, it can be inferred that most of the streets of Taipei City are blocks of mixed commercial and residential buildings. Therefore, most of the first floor areas

of the buildings are for commercial use. Crime rate statistics do not distinguish between theft-type crimes against stores and against people. Therefore, when the business activities are more vibrant (see Appendix), although implying that the crime rate can increase, vibrant business activities can directly cause house prices to increase. The violent-type crimes are directly and physically against the people, and the psychological burden on the people is relatively greater. Hence, it has a direct negative impact on house prices.

The star school coefficient of estimation is 0.016 at a 5 % significance level, suggesting that house prices will increase by 1.6% with every additional star school. These results are consistent with previous studies (Haurin & Brasington, 1996; Seo & Simons, 2009; Machin, 2011). Houses adjacent to a star school are regarded as undergoing the multiplication effect regardless of whether they are residential or for investment. Parents always expect that children who can study in star schools will provide some guarantee of future development. High school is the watershed. Many people decide to choose a vocational school system or the high school system. Therefore, parents will spare no efforts in investment. In order to send their children to star schools, parents will, in addition to registering their children as living at the home of a friend or relative who lives within the school's zone, also purchase houses within the given school zone.

In the spatial lag model, the spatial lag coefficient (ρ) is 0.872 at a 5% significance level, suggesting that house prices have a spatial mutual influence with adjacent regions. Namely, house prices in Taipei City are affected by sales prices in neighboring areas in a positive way. In the spatial error model, the spatial error coefficient (λ) is 0.992 at a 5% significance level, suggesting that there is an interference factor in the error item that causes spatial autocorrelation. Namely, Taipei City house prices will be affected by secondary factors in neighboring areas in a positive way.

It is noteworthy to see whether the spatial econometric model can actually reduce the coefficient overestimation and solve the estimation bias generated by the overlooking of spatial differences in the OLS. According to the empirical results as shown in Table 5, by comparing the OLS coefficient and the coefficients of spatial lag and spatial error models, most OLS coefficients are greater than those of spatial lag and spatial error models (e.g., BUILD, ROOM, BATH, CITYCEN, YEAR09, YEAR10, VIOLENCE, STARSCHOOL), and only a few coefficients are lower than those of the spatial lag and error models (DFLOOR, LIVROOM). When considering spatial differences in the spatial lag and spatial error models, the coefficients can better avoid any overestimation by using the conventional OLS.

Table 5. Empirical results analysis

Independent variable	OLS		Spatial lag model		Spatial error model	
	Coe.	t value	Coe.	t value	Coe.	t value
Intercept	5.537 **	198.604	0.345 **	3.178	4.337 **	9.469
AREA	0.022 **	35.078	0.022 **	37.496	0.022 **	38.835
AGE	-0.012 **	-8.789	-0.012 **	-10.234	-0.012 **	-10.199
AGES	0.001 **	10.315	0.001 **	11.546	0.001 **	10.874
BUILD	0.103 **	10.844	0.091 **	10.460	0.080 **	9.410
DFLOOR	0.087 **	7.644	0.088 **	8.575	0.089 **	8.795
ROOM	0.076 **	6.568	0.076 **	7.490	0.072 **	8.727
LIVROOM	0.105 **	6.161	0.116 **	7.446	0.117 **	7.621
BATH	0.059 **	4.529	0.036 **	5.360	0.029 **	6.007
PARK	-0.020	-1.501	-0.030	-2.533	-0.028	-2.361
CITYCEN	0.294 **	29.156	0.045 **	4.537	0.067 **	7.621
YEAR09	0.050 **	4.899	0.046 **	4.934	0.037 **	3.645
YEAR10	0.201 **	19.053	0.204 **	21.344	0.197 **	17.981
POLICE	0.001 **	4.158	0.001 **	2.210	0.001 **	3.149
LARCENER	0.001 **	10.211	0.001 **	7.077	0.001 **	3.023
VIOLENCE	-0.005 **	-10.133	-0.001	-1.319	-0.001	-1.342
STARSCHOOL	0.049 **	15.201	0.020 **	6.724	0.016 **	3.130
Spatial Lag(ρ)			0.872**	55.322		
Lambda(λ)					0.992 **	242.704
Likelihood ratio	-		2539.06 **		926.99 **	
Breusch-Pagan	2170.13 **		3040.29 **		3275.41 **	
	-608.33 **		-197.70 **			
Log likelihood	-661.19 **					

www.ccsenet.org/ijef
International Journal of Economics and Finance
Vol. 6, No. 1; 2014

SC	1460.88 **	1069.53 **	533.89 **
AIC	1354.40 **	1182.66 **	427.40 **
R^2	71.57 %	76.57 %	76.99 %

Note: the estimated coefficient value is the non-standardized estimated coefficient. ** and * suggest that the coefficient is significantly different from 0 at the 5% and 10% significance levels respectively.

6. Conclusion and Suggestions

This paper uses the spatial econometric model to estimate Taipei City house prices. According to the empirical results, the area coefficient of estimation is positive at a 5% significance level. The house age coefficient is negative at a 5% significance level, while the coefficient of its square is positive at a 5% significance level, suggesting that house prices will be lower if the houses are older. However, the amplitude of decrease will be smaller. The floor coefficient is positive at a 5% significance level, suggesting that prices of first floor houses will be higher. The coefficient of the total number of buildings is positive at a 5% significance level, suggesting that prices of houses above the sixth floor are higher. The coefficients of the number of rooms, number of living rooms and number of bathrooms are positive at a 5% significance level, suggesting that house prices will be higher if the number of rooms is greater. The coefficient of being located in the downtown area or not is at a 5% significance level, suggesting houses in the downtown area are higher priced. The coefficient of houses sold in 2009 and 2010 is positive, suggesting that houses sold in 2009 and 2010 have a higher price than the houses sold in 2008.

If the number of police personnel is greater, house prices will be higher; suggesting that law and order affects homebuyer demand as reflected by house prices. In the variables relating to the crime rate, the sign of a theft-type crime rate runs counter to expectations. The higher the theft-type crime rate is, the higher house prices will be. By observing business circles and consumption clustering areas, this paper finds that administrative regions with a higher theft-type crime rate have more highly clustered consumption areas. The star school coefficient is positive at a 5% significance level, suggesting that house prices in star school zones are higher than those in other areas. Barrow and Cecilia (2004) pointed out that school quality is one of the major considerations in the selection of houses. Parents with children and a higher income are willing to pay more for houses in exchange for getting the children in these high quality schools. The empirical results of this study confirmed the research results by Barrow and Cecilia (2004).

According to the empirical results, the spatial lag and error models' R^2 values increased by 5% and 5.42% respectively, as opposed to the OLS method, suggesting that the spatial econometric model has greater variance explanatory power than OLS. The model fitness values of AIC, SC, and Log likelihood all suggest that the spatial lag and error models have a higher level of fitness. Apparently, the coefficient estimations of many variables of the spatial lag and spatial error models are lower than those of the OLS model, indicating that the OLS model cannot explain the clustering and dependence of variables in terms of space. This, therefore, can result in an overestimation of the OLS coefficient, which also echoes the research conclusions of Chalermpong and Wattana (2009).

With Taipei City as the only analysis subject, this paper discusses the impact of crime rates and star schools. In the future, the research scope could expand to the entire Greater Taipei Area. The research period may also be lengthened. Moreover, more complete data, such as adding different neighboring characteristics, may be obtained so as to discuss their impact on house prices. In addition, there are many indicators representing the advantages and disadvantages of school zones, such as investment and performance. This paper uses the high threshold to represent the quality of school zones, which is similar to the performance perspective. Due to the limitations of obtaining school zone indicator data in Taiwan, future studies could attempt to obtain more indicators of school quality for a more in-depth study

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Notes

Note 1. Basu and Thibodeau (1998) argued that the existence of spatial dependence is due to adjacent houses generally having similar structural characteristics (as they were generally developed at the same time) and in a similar location environment. Therefore, they tested whether spatial autocorrelation appears in between the trading prices of independent houses.

Note 2. On the previous page, Moran' s I value is 0.1752, which is directly calculated by using the Moran' s I equation. The Moran' s I value on this page is calculated after the OLS regression estimation. Therefore, the values will be slightly different.

Appendix

Appendix 1. Theft-type crime and number of business areas

	Crime rate (case/100000 people)	Number of business areas
Zhongzheng District	1252.101	10
Zhongshan District	837.837	7
Datong District	893.278	6
Da'an District	765.100	12
Wanhua District	813.661	7
Xinyi District	655.762	8
Shilin District	543.021	6
Nangang District	568.198	0
Songshan District	551.172	3
Wenshan District	398.495	3
Beitou District	385.402	1
Neihu District	385.109	1

Source: Compiled by this study.

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