ISSN: 1648-715X / eISSN: 1648-9179

VILNIUS TECH
Vilnius Gediminas Technical University

INTERNATIONAL JOURNAL OF STRATEGIC PROPERTY MANAGEMENT

2024
Volume 28
Issue 1
Pages 1–15
https://doi.org/10.3846/ijspm.2024.20899

THE EFFECTS OF TRANSACTION HOTSPOTS AND FLIPPING HOTSPOTS ON HOUSING PRICES

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Article History:
- received 31 August 2023
- accepted 26 December 2023

Abstract. In contrast to much of the literature that focuses on the issue of spatial dependence in housing price research, this study addresses the spatial aggregation of housing transactions and analyzes the effects of transaction hotspots and short-term flipping hotspots on housing prices by using real housing transaction data in Taipei City, Taiwan. The empirical results show that after controlling for the effects of spatial dependence and individual housing attributes, the impact of transaction hotspot areas on housing prices is significantly negative, while the impact of flipping hotspot areas on housing prices is significantly positive. The results verify that the key to driving up housing prices lies in flipping activities. Furthermore, the results of the spatial quantile regression model show that low-priced residential properties are more sensitive to the spatial concentration of housing transactions and flipping transactions in the housing market. Our results have implications for the government's policy intending to control hot trade volumes to cool skyrocketing housing prices in a booming housing market. It is suggested that the government should pay attention to restraining short-term flipping activities in the housing market rather than setting constrains on housing transactions.

Keywords: housing prices, flipping, spatial aggregation, housing volume, hotspot analysis.

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1. Introduction

Housing transactions and housing prices have usually been the most important issues in housing market studies. Previous studies have indicated that housing transactions and housing prices interact (Rothenberg et al., 1991). In many cases, housing transactions can serve as an indicator of whether the housing market is hot or not. A traditional expectation based on this viewpoint suggests that the volume of housing transactions predicts housing prices; for example, a rapid increase in housing transactions induces a rise in housing prices (Hua et al., 2001; Yiu et al., 2009). A boom in housing transactions and housing prices in an area often indicates that the housing market is prospering; hence, more house buyers are attracted, including owner-occupiers and investors, and as a result, this drives housing prices up. However, it is difficult to distinguish rigid residential demand from speculative investing demand from observing housing transactions. By analyzing the frequency of housing transactions in a certain period of time, it can differentiate buyers' demand for owner-occupation or short-term speculation in the housing market (Depken et al., 2009).

In the housing market, the behavior of short-term buying and reselling properties with a profit can be seen as speculation or called flipping (LaCour-Little & Yang, 2023). Bayer et al. (2020) pointed out that investors who repeatedly buy and resell properties within two years are seen as flippers. Most flippers choose the location of property and time of investment and resell it when the housing price rises promptly (Yilmaz, 2014). Previous studies have indicated that short-term flipping in the housing market causes a boom in housing transactions and thus rapidly driving housing prices up, which is not conducive to the sound development of the housing market (Leung & Tse, 2017; Li et al., 2023). However, fewer studies have concerned the spatial content of housing flipping and examined its impact on housing prices.

Regarding the spatial concept of housing, adjoining housing units share similar environmental conditions, such as neighborhoods, parks, and open space. Housing prices of adjoining housing units are affected by each other, which is explained as the spatial dependence of house prices (Basu & Thibodeau, 1998; Case et al., 2004). In addition to the spatial dependence of housing prices, the concentration of traded residential properties also has spatial impacts (ripple effects) on the prices of adjacent properties. As stated earlier, previous studies have indicated that a rapid increase in housing transactions tends to drive up housing prices. In this sense, a boom in housing transactions in an area could have spatial effects on housing prices in this area and spreading effects on adjacent areas regarding a rise or a decrease in housing prices. Furthermore, the spatial concentration of housing transactions in an area may include the concentration of normal housing transactions and flipping transactions. Based on the above conditions, two questions are raised. Does a boom in these types of housing transactions have different impacts on housing prices? And how does the spatial concentration of these types of housing transactions affect housing prices? To answer these questions, this study uses housing transaction data in Taipei City, Taiwan, and employs a hot spot approach to examine the effect of the spatial concentration of normal transactions and of flipping transactions on housing prices.

Taiwan's housing market developed relatively early in Chinese culture, and it has atypical characteristics of "three highs", including high housing prices, a high vacancy rate, and a high ownership rate[1] (Chang & Chen, 2018). The three high conditions in Taiwan's housing market reveal the government's long-term skewed housing policy and ineffective management and intervention in the housing market and lead to flooded short-term flipping and speculation in the housing market (Chang & Hsieh, 2018). Chen et al. (2012) also indicate that the low interest rates provided business conglomerates and speculators with the opportunity of leverage to play the game in town, resulting in Taiwan's housing prices rising rapidly after 2004, particularly in Taipei City, the capital of Taiwan. The skyrocketing housing prices prompted the government to implement tax reform, including the introduction of a luxury tax[2] in 2011, the implementation of integrated housing and land tax[3] in 2016, and the new version in 2021 to hinder flipping and speculation in the housing market. However, the effects of these tax reforms on the housing market are under observation. More studies need to be devoted to the interpretation of flipping behavior and its effect on the housing market. Our results not only provide in depth discussions of how the spatial concentration of normal and flipping transactions works on housing prices but also provide insightful suggestions for housing policy in Taiwan as well as other countries that have suffered similar problems in the last decade.

[1] Despite sky-high house prices over the past few decades, homeownership rates in Taiwan are among the world's highest. Homeownership rates were 77% in 1985 and increased to 85% in 2016. The vacancy rate was also high, reaching 19.3% according to 2010 Population and Housing Census Report.

[2] The luxury tax levies a substantial tax (15% of the final selling price) on houses that are sold within two years of purchase.

[3] Taiwan government has implemented a significant tax reform measure known as the "integrated housing and land tax" in 2016 (and the new version in 2021). The integrated tax is an amendment to the existing Income Tax, with short-term arbitrageurs being heavily taxed. The tax is calculated based on the difference in value of real estate between the time of purchase and sale, with higher tax rates applied to properties sold within a shorter period of time (e.g. 45% of gains from houses that that have been bought and sold within 2 years).

The remainder of this paper is organized as follows. The next section reviews the literature. Section three introduces the research design, including the methodology, empirical model, and data. Section four presents and discusses the empirical results, and the final section contains concluding remarks and policy implications.

2. Literature review

The literature review contains two parts. The first part discusses housing transaction hotspots and the housing market; the second part discusses flipping in the housing market.

2.1. Housing transaction hotspots and housing market

One of the issues that industry, academia, and government all pay attention to is whether the housing market is hot or not. Housing markets show strong seasonal patterns, where hot markets with high prices and numerous transactions alternate with colder markets (Bø, 2018). In the field of real estate finance and economics, the overall "hot" condition of residential real estate transactions is mostly described through trading volume or liquidity (Kluger & Miller, 1990; Kalra & Chan, 1994; Yang & Yavas, 1995; Jud et al., 1996, and Schilling, 1996). If houses can be sold quickly in the market, it means that the market is hot. For example, Krainer (2001) offered a theoretical framework of liquidity in housing markets and used three indicators to characterize a hot period (rising prices, quick selling times, and higher trading volumes). Carrillo and Pope (2012) also used the time on the market (TOM) to measure the condition of the housing market. They found that the Washington D.C. area experienced a hot market in 2003 and a cold market in 2007.

Market conditions can be categorized into thick markets and thin markets. Ngai and Tenreyro (2014) propose a search-and-matching model with thick-market effects, i.e., where the expected match quality is positively correlated with the number of houses for sale. They also find empirical support (of the US and UK housing markets) for the idea that average match quality is higher for houses transacted in hot markets than in cold markets. Huang et al. (2018) employ the turnover rate to measure housing market activities. Their primary unit of analysis is real estate development (RED), which is usually a cluster of residential buildings constructed by the same developer in a nearby area around the same period. They find that different REDs have different turnover rates and identify several empirical determinants of the turnover rates. Moreover, they find that the scale of the RED is not statistically significant, and hence, the "thick market externality" might not be present in their sample.

A related issue is why some spots are hot, and others are not. One factor is location (for instance, Bilal & Rossi-Hansberg, 2021). However, there are other empirical determinants (for example, Huang et al., 2018). In the case of Hong Kong, Leung et al. (2014) find that developers choose to install different bundles of amenities, including the physical layout of the housing units, in different locations. In other words, it is a choice of the developer. In the case of Beijing, Fan et al. (2022) find that developers in different financial conditions will (a) choose different districts to develop, (b) choose different types of buildings to develop, and (c) adopt different pricing strategies in the selling stage. Again, it reinforces the point that developers choose which spots are hot and which are not.

The aforementioned literature predominantly concentrates on the period of a hot market (seasons or years), transaction conditions (quantity and speed), and the reasons why certain spots are deemed hot. However, there are few studies that analyze the hot market from the spatial perspective of transaction clustering and further delve into the influence of housing transaction hotspots on housing prices. Spatial techniques have been widely applied in housing research with the rapid progress of spatial software programs in the last three decades (Anselin, 1992; Anselin & Bera, 1998; Dubin et al., 1999). Spatial analysis allows us to solve complex location-related problems and explore data information from a geographic perspective. The most common method is spatial clustering analysis or hotspot analysis, which can detect unusual clusters of events, activities, or states in a space (Wang & Varady, 2005; Musil et al., 2022).

In the past three decades, a large number of studies have addressed the spatial dependence of housing prices and have applied spatial techniques to improve spatial correlation in estimating housing prices (for example, Basu & Thibodeau, 1998; Case et al., 2004; Bourassa et al., 2007, 2010). However, less attention has been given to discuss the effect of the spatial concentration of the number of residential transactions on the housing market. Spatial concentration in housing transactions, might reflect people's reactions to psychological uncertainty, resulting in herding behaviors and market transaction clustering, which could be described as transaction hotspot areas (Xu et al., 2019). A rapid increase in housing transactions in an area should have spatial effects on housing prices in this area and spreading effects on adjacent areas regarding a rise or a decrease in housing prices. Therefore, our paper employs a hotspot analysis approach to examine the spatial effects of housing transaction hotspots on housing prices.

2.2. Flipping in the housing market

Flipping in the housing market describes when an investor purchases a property for a relatively low price, sometimes conducts rehabilitation or renovation activities and then sells the property at a profit (Depken et al., 2009). Some studies, such as Depken et al. (2011) and LaCour-Little and Yang (2023), indicate that flipping in the housing market often drives up prices rapidly and causes volatile turnover (Leung et al., 2019), which is not conducive to the sound development of the housing market and does not help meet the living needs of the people. Anacker and Schintler (2015) employed a case study and visualized potential house-flipping transactions in the city of Mansfield, Ohio, using social network analysis (SNA) techniques. Leung and Tse (2017) included the role of arbitrage middlemen[4] in the housing market search model. The analysis indicated that flipping tends to occur in sluggish and tight markets, but the numerical results showed that flipping in a tight and liquid market could be wasteful since the efficiency gain from any faster turnover is not large enough to offset the loss from more houses being left vacant.

Furthermore, Wong et al. (2022) find that buying and reselling within three months produces a gross return of 6% above the market. Li et al. (2023) investigate the externalities of residential property flipping and find that flippers impose a significant positive impact on the price of neighboring nonflipped properties in an up market but a significant negative effect in a down market. Such a procyclical impact of flipping activity contributes to the volatility of housing prices and thus increases the likelihood of a mortgage crisis. The finding is probably limited by the availability of data and methods that those previous studies do not consider the spatial concept of flipping transactions and discuss their impacts on the housing market. As a result, this study uses real transaction data and employs spatial techniques to analyze the effect of the spatial concentration of flipping transactions on housing prices.

3. Research design

3.1. The model

The distribution of housing transactions is known to have a spatial dimension; that is, a map of point locations of housing transactions often reveals spatial patterns or clusters. In this study, we first employ hotspot analysis to explore the spatial distributions of housing transactions and short-term flipping behaviors in the housing market. Then, the spatial autoregression model is utilized to estimate the effects of transaction hotspot areas and flipping hotspot areas on housing prices. Finally, we use the spatial quantile regression model to examine the impacts of transaction hotspot areas and flipping hotspot areas on housing prices with various quantiles. These methods are described in the following.

(1) Hotspot analysis

A hotspot is defined as an area that has a higher concentration of events compared to the expected number or probability given a random distribution of events. Hotspot detection evolved from the study of point distributions or spatial arrangements of points in a space (Chakravorty, 1995). When examining point patterns, the density of points within a defined area is compared against a complete spatial randomness model, which describes a process

[4] The middlemen are the so-called "flippers" who attempt to profit from buying low and selling high in the short-term.

in which point events (here, housing transactions) occur completely at random.

In this study, the hot spot analysis method calculates the Getis-Ord G_i^* statistic for each transaction sample in the housing transaction dataset. The results of *z*-scores and p-values present where transactions with either high or low values cluster spatially. This method works by looking at each transaction sample within the context of neighboring transaction samples. A transaction sample with a high value is interesting but may not be a statistically significant hot spot. To be a statistically significant hot spot, a transaction sample must have a high value and be surrounded by other high values transaction samples in a given area. In this study, the area is delineated by a 50×50 meter (50×50 m) grid, about a street block in Taipei City. A hotspot area is defined as where the area is concentrated of housing transaction samples with statistically significant Getis-Ord G_i^* values and is surrounded by other transaction samples with high values. A hotspot area of housing transactions indicates a statistically significant and high concentration of housing transactions. The use of Getis-Ord G_i^* is more objective and accurate than the use of density of housing transactions to indicate the hotspot area.

In Equation (1), the Getis-Ord G_i^* statistic is presented as a *z* score,

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij} x_j - \bar{X} \sum_{j=1}^{n} w_{ij}}{S \sqrt{\frac{n \sum_{j=1}^{n} w_{ij}^2 - (\sum_{j=1}^{n} w_{ij})^2}{n-1}}}, \tag{1}$$

where

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \text{ and } S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\bar{X}\right)^2}, \tag{2}$$

where: n is the total number of observations; x_j is the attribute value for spatial unit j; w_{ij} is the spatial weight between spatial units i and j,

$$w_{ij} = \frac{\beta_{ij}{}^{b}}{d_{ij}{}^{a}}, \tag{3}$$

where: d_{ij} is the distance between spatial units i and j; β_{ij} is the proportion of the interior boundary of unit i which is in contact with unit j; a and b are the parameters. The calculation of spatial weights matrix is based on distance band and employed by Geoda software.

(2) Spatial lag model

This study employs the spatial autoregression model to improve the problem of spatial dependence among housing prices and to increase the estimation accuracy of the housing price model. Two spatial autoregression models are widely known: the spatial lag model and the spatial error model. By examining the goodness of fit of these two models, it was found that the pseudo R^2 of the spatial lag model is higher than that of the spatial error model and the Akaike information criterion (AIC) for the spatial lag model is lower than that of the spatial error model[5]. As a result, the spatial lag model has better estimation accuracy and thus is used in this study.

The spatial lag model uses a spatial lag variable to present spatial dependence in house prices caused by spatial externalities and spillover effects. The term "lag" means spatial lag rather than time lag in house prices, which means that activities in a spatial unit are affected by adjoining activities and have effects on other activities in the spatial unit (Anselin, 1988). The function of our spatial lag model is presented as in Equation (4),

$$LnP = \alpha + \rho W\left(LnP\right) + \sum_{k=1}^{4} \beta_k X_k + \varepsilon,\ \varepsilon \sim N\left(0, \sigma^2 I\right), \tag{4}$$

where the dependent variable is housing price in natural log form (LnP); α denotes the constant term; ρ represents the coefficient of spatial lag variable; $W(LnP)$ denotes the spatial lag variable; β_k denotes the regression coefficients of independent variables of X_k, and ε is the error term. X_k denotes four types of attributes, encompassing physical attributes, locational attributes, transaction years and quarters, and hot spot attributes. Except for the hot spot variables, the others are considered as control variables. The physical attributes comprise the building floor area, trading floor, total number of stories, number of bathrooms, and age of the dwelling. The locational attributes include administrative district dummies, distance to the nearest MRT station, and distance to the city center.

Different from the OLS regression model, the spatial lag model adds the spatial lag variable $W(LnP)$ to the regression model. This spatial lag variable is derived by the explanatory variable multiplied by the spatial weight matrix (W). The coefficient of the spatial lag variable ρ is used to test spatial autocorrelation among house prices. When $\rho \neq 0$, a significant spatial autocorrelation exists in house prices.

The spatial weight matrix is a $n \times n$ matrix with spatial weights is shown in Equation (5),

$$W = \begin{bmatrix} 0 & w_{12} & \dots & w_{1n} \\ w_{21} & 0 & \dots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \dots & 0 \end{bmatrix}, \tag{5}$$

where: w_{ij} denotes the spatial weights of unit i and unit j; n is the number of observations.

(3) Spatial quantile regression model

Based on the spatial lag model and the quantile regression model, the spatial quantile regression model allows the heterogeneity of influence characteristics on the explained variable and accounts for the spatial dependence. It has

[5] The pseudo R^2 of the spatial lag model and the spatial error model are 0.859 and 0.855, respectively. The AIC for the spatial lag model and the spatial error model are 14,678.08 and 14,737.21, respectively. The higher pseudo R^2, the better goodness-of-fit, while the lower AIC, the smaller estimation error.

been widely applied to examine the varying effects of housing features on conditional low- or high-priced housing (Zietz et al., 2008; Liao & Wang, 2012; Wen et al., 2019; Gu & You, 2022). The model is presented in Equation (6),

$$LnP_{\theta} = \alpha_{(\theta)} + \rho_{(\theta)} W\left(LnP\right) + \sum_{k=1}^{4} \beta_{k(\theta)} X_k + \varepsilon_{\theta},\ \varepsilon_{\theta} \sim N\left(0, \sigma^2 I\right), \quad (6)$$

where θ denotes quantiles. The other symbols, such as LnP, α, ρ, $W(LnP)$, β_k, X_k, and ε, are the same as stated in Equation (4).

3.2. The data

The data come from the transaction price registration database published by the Ministry of Interior since August 2012. This official database contains detailed information, e.g., actual transaction prices, addresses, and housing attributes. Covering the residential transactions in Taipei City with the period ranging from the third quarter of 2012 to the end of 2021. A total of 62,140 housing transaction samples are used in this study. To determine whether a housing has undergone repeat transactions, specific criteria are applied to both transaction instances, encompassing shared attributes such as doorplate address, land transfer area, building transfer area, completion month and year of construction, floor, total story, building layout, and building type. Within all housing transaction samples, 10.5% of them accounting for 6,532 observations were resold at least once in the last decade. Taipei City is the most important political and economic center and the capital of Taiwan, acting as the leader of the Taiwan housing market (Lee et al., 2014). Housing transactions in Taipei City are hot and potentially hyped (Teng et al., 2016), making it a particularly suitable research object for this study. The spatial distribution of housing transactions in Taipei City is shown in Figure 1. It is obvious that there exists a spatial aggregation of housing transactions, verifying that the conjecture of this study is feasible.

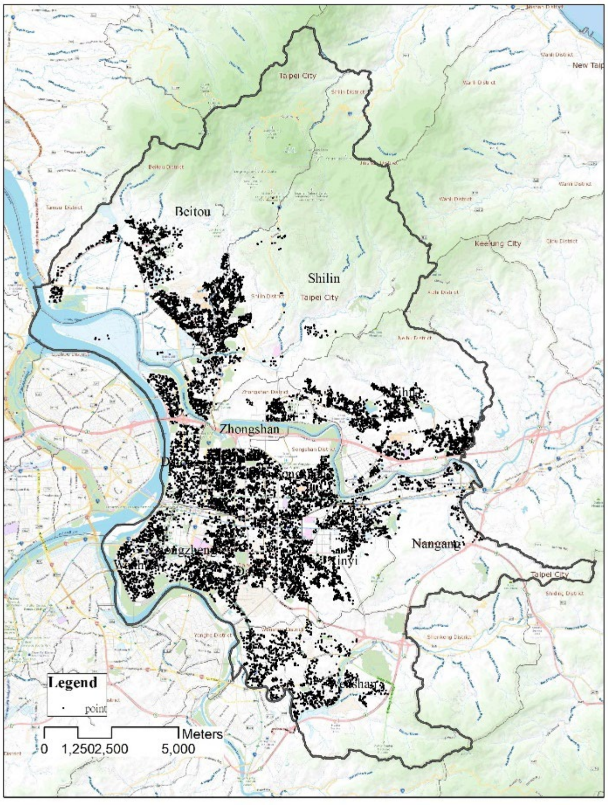

Figure 1. Spatial distribution of housing transactions in Taipei City

3.3. The variables

Based on the hotspot analysis, this study defines two important dummy variables to describe the locational attributes of transaction hotspot areas and flipping hotspot areas. The former (*THA*) is the dummy variable indicating that the property is located in a transaction hotspot area, while the latter (*FHA*) indicates that the property is located in a flipping hotspot area.

The dependent variable of the empirical model is the real housing price, which is the registering transaction prices deflated by the consumer price index (CPI). Except for *THA* and *FHA*, the other controlling variables include physical attributes, locational attributes, administrative district dummies, and trading time (year × quarter) dummies.[6] The physical attributes include the building floor areas (*Area*), the trading floor (*Floor*), the total story (*TStory*), the number of bathrooms (*Bathroom*), and the dwelling age (*Age*). The locational attributes are the distance to the nearest MRT station (*Dist. MRT*) and the distance to the city center (*Dist. CC*)[7]. The descriptive statistics of the samples are summarized in Table 1.

With respect to the dependent variable, the average real housing prices are 25.4 million New Taiwan dollars (TWD).[8] The maximum prices are over 463 million TWD (approximately 15.4 million USD), while the minimum prices are approximately 1.58 million TWD (approximately

[6] Taipei City consists of 12 administrative districts. The 12 administrative districts could serve as representatives of low-price and high-price areas. For instance, districts like Wanhua, Beitou, and Wenshan are considered relatively low-price areas, with an average price per ping of around five hundred thousand in 2022. Datong, Shilin, Neihu, and Nangang represent middle to lower-price areas, with an average price per ping of around six hundred thousand. Zhongshan, Songshan, and Xinyi are classified as middle to high-price areas, with an average price per ping of approximately seven to eight hundred thousand. On the other hand, Da-an and Zhongzheng are relatively high-price areas, with an average price per ping exceeding nine hundred thousand in 2022. Here takes the Wanhua District as the base and the other 11 administrative districts are controlling dummies. With respect to the trading year and quarter, the controlling variables are 37 dummy variables from 2012Q3 to 2021Q3, taking 2021Q4 as the base.

[7] This paper uses the MRT Zhonghsiao-Fushin Station as the city center since it is located in geography center of Taipei City and the passenger flow in this station is the greatest.

[8] The exchange rate between USD and TWD is floating, range from 27.5 TWD/USD to 33.5 TWD/USD over the past decade. The average real housing prices of our samples are 25.4 million TWD, approximately 846 thousand USD (based on the exchange rate of 30 TWD to 1 USD).

Table 1. Descriptive statistics of samples

Variable	Means	Std.	Max.	Min.
Real housing price (1,000 NTD)	25,439.453	24043.389	463,054.197	1,579.953
Building floor areas (m^2)	116.458	67.880	694.971	18.463
The trading floor	6.283	4.194	36	1
The total story	10.880	5.480	42	2
Number of bathroom	1.607	0.668	6	0
Dwelling age (year)	17.408	14.989	57.712	0.010
Distance to nearest MRT station (100 m)	6.268	4.626	49.495	0.013
Distance to city center (100 m)	48.774	26.879	126.316	0.454
Located in transactions hotspot areas (THA)	0.299	0.458	1	0
Located in flipping hotspot areas (FHA)	0.010	0.098	1	0
Located in THA × FHA	0.003	0.051	1	0
Located in Zhongzheng Dist.	0.051	0.220	1	0
Located in Datong Dist.	0.041	0.198	1	0
Located in Zhongshan Dist.	0.151	0.358	1	0
Located in Songshan Dist.	0.065	0.247	1	0
Located in Da-an Dist.	0.041	0.198	1	0
Located in Wanhua Dist.	0.084	0.278	1	0
Located in Xinyi Dist.	0.062	0.242	1	0
Located in Shilin Dist.	0.076	0.265	1	0
Located in Beitou Dist.	0.102	0.302	1	0
Located in Neihu Dist.	0.143	0.351	1	0
Located in Nangan Dist.	0.052	0.222	1	0
Located in Wenshan Dist.	0.101	0.302	1	0
Transacted in 2012	0.071	0.256	1	0
Transacted in 2013	0.173	0.379	1	0
Transacted in 2014	0.133	0.340	1	0
Transacted in 2015	0.010	0.300	1	0
Transacted in 2016	0.089	0.285	1	0
Transacted in 2017	0.079	0.270	1	0
Transacted in 2018	0.081	0.272	1	0
Transacted in 2019	0.090	0.286	1	0
Transacted in 2020	0.099	0.299	1	0
Transacted in 2021	0.084	0.277	1	0
Transacted in Q1	0.196	0.397	1	0
Transacted in Q2	0.264	0.441	1	0
Transacted in Q3	0.250	0.433	1	0
Transacted in Q4	0.290	0.454	1	0
Sample sizes: 62,140				

52.6 thousand USD). Among the physical attributes of the dwellings, the average building floor area is 116.46 m^2, while the average number of bathrooms is 1.6 rooms. The average trading floor is over the 6th floor, while the average total story is over 10 stories. The average dwelling age is 17.4 years old, while the oldest dwelling is over 57 years old and the newest dwelling is just over 1 month old.

Regarding locational attributes, the average distance from the property to the nearest MRT station is 626.8 meters. The average distance from the property to the city center is over 4.88 km. With respect to hotspot areas, approximately 30% of the total samples are located in transaction hotspot areas. The properties located in the transaction hotspot areas have experienced a statistically significant high level of (adjacent) trading volume during the past decade, providing relatively sufficient information for the following transactions. It is noted the identification of flipping hotspot areas is based on the samples that were resold within two years during the research period. Among 6,532 repeated sale samples, 3,302 samples were resold within two years, accounting for 50.6% of total repeated sale samples and 5.3% of total housing transaction samples. Among these flipping samples, approximately one-fifth were located in statistically significant high-flipping transaction areas called hotspot areas, which accounted for 1% of the total housing transaction samples. On the other hand, approximately four-fifths of flipping samples are distributed randomly in Taipei City.

Among the 12 administrative districts, Zhongshan District, located in older city areas, has the greatest share of housing transaction samples, accounting for 15.1% of the total samples, followed by Neihu District and Wenshan District, which are located in suburban areas, accounting for 14.3% and 10.1% of the total samples, respectively. With respect to the transaction years, Taipei's housing market experienced the greatest number of housing transactions in 2013, followed by 2014, indicating that there was a boom in the housing market in these two years. Housing transactions also slightly increased during 2019 and 2020. In terms of transaction seasons, the fourth quarter experienced the greatest number of housing transactions, followed by the second quarter, and then the third quarter. The first quarter recorded the fewest housing transactions due to the Lunar New Year holiday.

4. Hotspot analysis and empirical results

This section consists of three parts. The first part discusses the results of hotspot analysis; the second part analyzes the results of housing price models, including the ordinary least squares (OLS) regression model and the spatial regression model; and the third part discusses the results of the spatial quantile regression model.

4.1. Hotspot analysis of housing transactions

This study applies hotspot analysis to identify transaction hotspot areas and flipping hotspot areas in the housing market.

(1) Housing transactions hotspot areas

As mentioned earlier, this study uses the hotspot analysis tool in the GIS program to verify the spatial relationship of a housing transaction sample within the context of neighboring transaction samples by calculating the Getis-Ord G_i^* statistic for each housing transaction sample in a given area. The area is delineated by a 50×50 m grid, about a street block in Taipei City. Of the 109,313 grids in the city, 10,255 grids contain housing transaction samples, which account for 9.4% of the city area. Among 10,255 grids with housing transaction samples, the average transaction samples are 6.07 samples. The maximum number of samples in a grid is 760 samples. A hotspot area is defined as where the area is concentrated of housing transaction samples with statistically significant Getis-Ord G_i^* values and be surrounded by other transaction samples with high values as well. The results of the hotspot areas of housing transactions in Taipei City are shown as blue areas in Figure 2. The hotspot areas of housing transactions (blue areas) account for 30% of the housing trading volume, displaying spatial clusters and a high concentration of housing transactions.

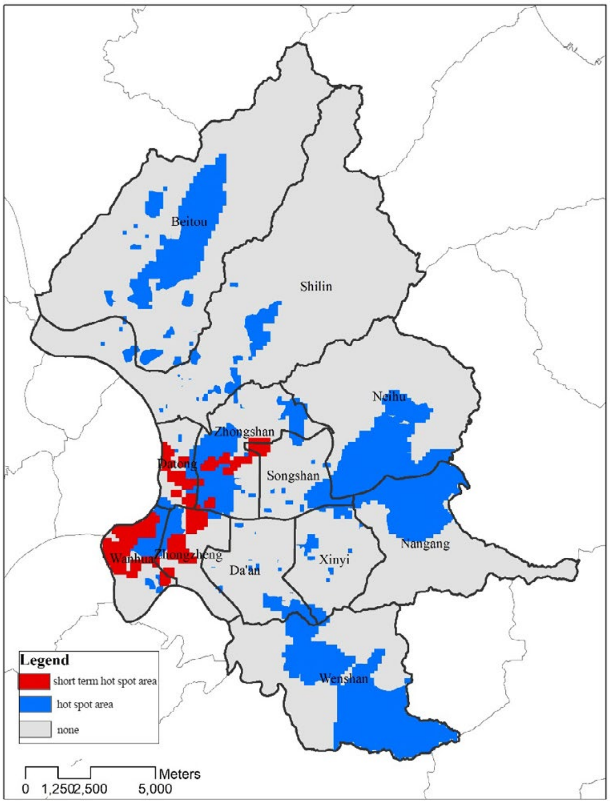

Figure 2. Transaction hotspot areas and flipping hotspot areas in Taipei City

As shown in Figure 2, the transaction hotspot areas are concentrated in old central areas of the city, such as Zhongshan District and Wanhua District, and in some suburban areas (Beitou District, border areas of Neihu and Nangang Districts, and Wenshan District). Moreover, most hotspot areas of housing transactions are located in lower housing price areas in Taipei City. Since housing prices in Taipei City have greatly risen in the last decade, many homebuyers were not able to afford to high-price houses; as a result, lower-priced housing transactions are greater and hotter than mid- to high-priced housing transactions in Taipei City.

(2) Housing flipping hotspot areas

This study also evaluates the hotspot areas of short-term flipping transactions in the housing market. As mentioned earlier, short-term flipping is defined as a property that has been flipped within two years. To focus on the number of housing flips, this study first filters the number of properties that have been transacted at least once from the total housing transaction samples. During the sample period, a total of 6,532 samples were resold at least once, accounting for 10.5% of the total housing transaction samples. Among these repeated-sale properties, we then select properties that have been resold at least once within two years as defined housing flipping. A total of 3,302 flipping samples were filtered from 6,532 repeated sales, accounting for 50.3% of the total repeated-sale samples.[9] This figure illustrates the gravity of the issue of flipping in Taipei's housing market. By using a hot spot analysis approach to calculate the Getis-Ord G_i^* statistic for each flipping sample in 50×50 m grid areas in the city, the hotspot areas of housing flipping are identified as red areas in Figure 2.

As shown in Figure 2, the red areas account for approximately 50% of areas with repeated sale samples and account for 1% of total housing transaction areas in the city, representing the most significant and high concentration of flipping transactions in the housing market over the past decade. The transaction hotspot areas and flipping hotspot areas do not exactly overlap. Compared to the hotspot areas of housing transactions (the blue areas), the hotspot areas of housing flipping are more likely to be concentrated in western areas of the city, such as Zhongshan District, Datong District, Zhongzeng District, and Wanhua District, where they are old city center areas in Taipei City. Furthermore, most flipping hotspot areas are located in relatively lower-priced areas. This implies that lower-priced properties are more likely to be flipped than high-priced properties in Taipei City.

4.2. Results of OLS model and spatial lag model

Regarding the housing price model, this study employs the spatial lag model to improve the spatial dependence of housing prices.[10] The results of the OLS and the spatial autoregression models are shown in Table 2. The full model results are shown in the Appendix. The results show that there is a significant and positive coefficient of spatial autocorrelation, suggesting that spatial autocorrelations exist significantly among housing prices. Thus, using the spatial lag regression can alleviate the problem of spatial dependence among housing prices and therefore improve the model goodness-of-fit. As shown in Table 2, the goodness-of-fit of the spatial lag model is better than that of the OLS model, while the *R*-square of the spatial lag model is slightly higher than that of the OLS model.

In both models, the directions and coefficients of the controlling variables, such as district dummy variables, are as expected and consistent with prior studies. An increase of one square meter in floor area increases housing prices by 0.8%, and an increase of one bathroom rises housing prices by approximately 6%. In contrast, an increase of one

Table 2. Results of OLS model and spatial autoregression models

Model	OLS model		Spatial lag model		Spatial error model	
Variable	Coeff.	*t* value	Coeff.	*z*-statistic	Coeff.	*z*-statistic
Constant	16.149	1394.93***	16.184	1426.16***	16.224	1350.06***
Area	0.008	315.66***	0.008	316.60***	0.007	179.92***
Floor	–0.0004	–1.05	–0.0001	–0.37	–0.0008	–2.33**
TStory	–0.0003	–1.01	–0.0004	–1.33	–0.0009	–2.69***
Bathroom	0.059	24.31***	0.060	25.31***	0.061	25.42***
Age	–0.011	–118.36***	–0.011	–121.44***	–0.011	–114.10***
Dist. MRT	–0.011	–40.04***	–0.011	–39.90***	–0.011	–37.84***
Dist. CC	–0.004	–32.22***	–0.003	–27.49***	–0.003	–31.16***
THA	**–0.102**	**–34.74*****	**–0.099**	**–34.56*****	**–0.101**	**–34.42*****
FHA	**0.014**	**1.08**	**0.022**	**1.70***	**0.020**	**1.55**
THA × FHA	**0.042**	**1.68***	**0.050**	**2.02****	**0.032**	**1.30**
Administrative districts	Yes		Yes		Yes	
Trading years × quarters	Yes		Yes		Yes	
Spatial autocorr. coeff.	–		0.196	52.50***	0.056	22.32***
(Pseudo) *R*-square	0.853		0.859		0.855	
F value	6215.69***		–		–	
AIC	14781.55		14678.08		14737.21	

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The number of observations is 62,140. The results of controlling dummies of the administrative district and trading year and quarter are provided in the Appendix.[11]

9 Of the 62,140 transactions in our sample, 3,302 occurred within 2 years. The proportion of 5.31% is larger than the corresponding ratio (3.13% = 3,133/100,076) in the paper of Li et al. (2023) which using the dataset of residential property transactions in Clark County, Nevada in the USA for the period 2003–2013.

10 The Moran's I for housing transaction prices is 0.1741, with a *z*-score of 859.99, indicating a significant positive spatial correlation among housing transaction prices.

11 As expected, the results show the housing prices in all 11 districts are significantly higher than in the Wanhua District. In addition, housing prices decreased compared to 2021, indicating a steady increase of housing prices over the past decade.

year in dwelling age decreases housing prices by approximately 1.1%. The distance to the nearest MRT station and the distance to the city center all have negative effects on housing prices, which indicates that the closer to the MRT station and to the city center, the higher the housing prices.

The coefficient of *THA* is –0.099 and significant in the spatial lag model, indicating that housing prices in transaction hotspot areas decrease 9.9% compared to those not in hotspot areas. This is probably because of the price comparison effect; that is, when there are many properties for sale in the market, the competitive effect for on-sale properties usually makes transaction prices down. Such results are compatible with the findings of Deng et al. (2022). Properties in the areas of many transactions have more sufficient information and more competitors and thus reduce their transaction prices.

Furthermore, the coefficient of *FHA* in the spatial lag model is 0.022, denoting that housing prices increase up to 2.2% in hotspot areas of flipping activities. These results are in line with the viewpoints of short-term flipping speculation in the housing market (Leung & Tse, 2017; LaCour-Little & Yang, 2023). House flipping increases housing prices and harms sound markets.[12] The summarizing effect of both THA and FHA on housing prices is –0.027 (–0.099+0.022+0.050), denoting that housing prices decrease by 2.7% in both hotspot areas of housing transactions and hotspot areas of flipping activities. Since properties in the FHA drive up neighboring prices, the negative effect of the interactive THA and FHA on housing prices is less than that on THA only. In short, the above results suggest that a high concentration of flipping activities in the housing market, rather than a high concentration of normal housing transactions, is an important driving force of rising housing prices in the housing market of Taipei City.

4.3. Results of the spatial quantile regression model

This subsection discusses the results of the spatial quantile regression model, which estimates the effects of transaction hotspot areas and flipping hotspot areas on various quantiles of housing prices with the consideration of spatial autocorrelation. The results are summarized in Table 3. The full model results are also shown in the Appendix. The trading floor (*Floor*) and total story (*TStory*) have positive effects on properties in middle to high housing price levels, showing that the influence of being located on a high floor and high-rise buildings on housing prices increases with a rise in housing price quantile levels. The number of bathrooms (*Bathroom*) has a greater influence on properties at lower housing price levels than at higher price levels.

Table 3. Results of the spatial quantile regression model

Model	Low		………… Housing prices …………						High	
	0.1 q		0.25 q		0.5 q		0.75 q		0.9 q	
Variable	Coeff.	*t* value	Coeff.	*t* value	Coeff.	*t* value	Coeff.	*t* value	Coeff.	*t* value
Constant	15.916	582.66***	16.067	991.19***	16.155	1303.56***	16.236	1297.69***	16.334	1150.88***
Area	0.008	131.06***	0.008	230.96***	0.008	305.09***	0.008	300.55***	0.008	265.16***
Floor	–0.002	–2.15**	0.001	1.51	0.001	3.91***	0.002	5.064***	0.002	3.27***
TStory	–0.004	–5.40***	–0.001	–3.01***	0.001	3.31***	0.003	7.32***	0.003	6.37***
Bathroom	0.069	12.16***	0.061	17.98***	0.055	21.54***	0.054	20.79***	0.049	16.63***
Age	–0.012	–55.95***	–0.012	–88.20***	–0.011	–105.21***	–0.010	–100.58***	–0.010	–86.66***
Dist. MRT	–0.012	–17.80***	–0.013	–33.05***	–0.011	–38.23***	–0.010	–32.26***	–0.009	–25.01***
Dist. CC	–0.002	–9.48***	–0.003	–16.04***	–0.003	–26.20***	–0.004	–29.40***	–0.004	–26.04***
THA	**–0.122**	**–17.62*** **	**–0.124**	**–30.11*** **	**–0.097**	**–30.80*** **	**–0.061**	**–19.22*** **	**–0.038**	**–10.64*** **
FHA	**0.069**	**2.24** **	**0.050**	**2.74*** **	**0.014**	**1.69* **	**–0.018**	**–1.26**	**–0.024**	**–1.51**
THA × FHA	**–0.023**	**–0.40**	**0.037**	**1.07**	**0.056**	**2.10** **	**0.089**	**3.30*** **	**0.045**	**1.45**
Administrative districts	Yes		Yes		Yes		Yes		Yes	
Trading years × quarters	Yes		Yes		Yes		Yes		Yes	
Spatial autocorr. coeff.	0.163	18.14***	0.185	34.70***	0.200	48.77***	0.214	51.82***	0.217	46.49***
(Pseudo) *R*-square	0.577		0.606		0.641		0.671		0.693	

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The number of observations is 62,140. The results of controlling dummies of administrative district and trading year and quarter are provided in the Appendix.

[12] See article titled "How Tales of 'Flippers' Led to a Housing Bubble" by Robert Shiller, at *Economist's View* on May 18, 2017, available from https://economistsview.typepad.com/economistsview/2017/05/how-tales-of-flippers-led-to-a-housing-bubble.html

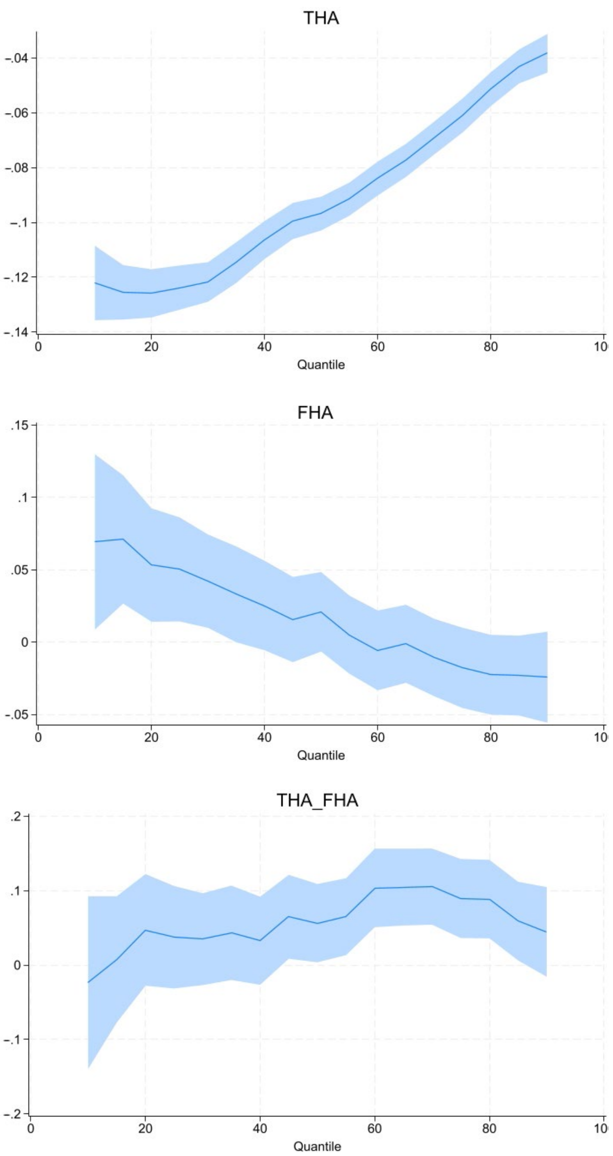

Figure 3. The coefficients of *THA*, *FHA*, and *THA* × *FHA* in different quantiles

The spatial quantile regression allows us to assess the effects of THA at specific quantiles of the dependent variable. Thus, we estimate the effects of THA in both low-priced (10th quantile) and high-priced (90th quantile) areas. The results consistently show negative and significant coefficients for THA across all quantiles, indicating that THA remains a significant negative factor not only in low-priced areas but also in high-priced areas. In Table 3, for example, in the 0.1 q column (representing the 10th percentile of Taipei City housing prices), the coefficient for THA is –0.122 (t = –17.62; p-value < 0.01). Similarly, in the 0.25 q column (representing the 25th percentile of Taipei City housing prices), the coefficient for THA is –0.124 (t = –30.11; p-value < 0.01). These results demonstrate that transaction hotspots are not synonymous with low-priced areas, as THA remains significantly negative in low-priced regions even after controlling for administrative districts and distance-related spatial variables.

Since this study addresses the influences of transaction hotspots and flipping hotspots on housing prices, the coefficients of *THA* and *FHA* in different quantiles are depicted in Figure 3. It is interesting to observe that the coefficients of *THA* are –0.122, –0.124, –0.097, –0.061, and –0.038 at quantiles of 0.1 q, 0.25 q, 0.5 q, 0.75 q, and 0.9 q, respectively.[13] That is, these transaction hotspot areas have greater negative impacts on properties at lower price levels than at middle to high price levels. In other words, prices in lower-priced properties are more likely to be reduced where they are located in areas with a high concentration of housing transactions.

Furthermore, the coefficients of *FHA* are 0.069, 0.050, 0.014, –0.018, and –0.024 at quantiles of 0.1 q, 0.25 q, 0.5 q, 0.75 q, and 0.9 q, respectively. This indicates that flipping activities have greater positive effects on properties at lower price levels than at middle to high price levels. The lower-priced properties are more likely to be flipped and thus raise their prices in Taipei's housing market. In addition, the coefficients in the 0.75 and 0.9 quantiles are insignificant, indicating that the influences of flipping activities are insignificant and weak in higher priced properties. The effects of properties in both THA and FHA are significant on housing prices in the 0.5 and 0.75 quantiles, respectively. The interactive effect is greater in the 0.75 quantile than in the 0.5 quantile. These results indicate that the interactive effect of THA and FHA have greater and significant influences on middle- to high-priced houses in Taipei's housing market. Simply stated, with a rise in housing price level, the negative effects of transaction hotspots and the positive effects of flipping hotspots on housing prices decrease. Low-priced residential properties are more sensitive to the spatial concentration of housing transactions and flipping transactions in the housing market of Taipei City.

5. Conclusions

In contrast to much of the literature that focuses on the issue of spatial dependence in housing price research, this study addresses the spatial aggregation of housing transactions and analyzes the effects of transaction hotspots and short-term flipping hotspots on housing prices by using real housing transaction data in Taipei City, Taiwan. The empirical results show that after controlling for the effects of spatial dependence and individual housing attributes, the impact of transaction hotspot areas on housing prices is significantly negative, while the impact of flipping hotspot areas on housing prices is significantly positive. The results verify that the key to driving up housing prices lies in flipping activities. Furthermore, the results of the spatial quantile regression model show that low-priced residential properties are more sensitive to the spatial concentration

[13] As shown in Figure 3, the trend of the coefficients of *THA* is rising. However, the coefficients of *THA* are negative, so the rising trend means the negative influences of transaction hotspot areas on housing prices are decreased.

of housing transactions and flipping transactions in the housing market.

Hot spot analysis has been widely used to analyze the spatial correlation of housing prices in the housing market, but less research has addressed the effect of "hotspot areas" of two types of housing transactions on housing prices. This study provides another perspective to analyze the relationships between trade volumes and prices in housing market research. The results off two important implications for government. First, areas of hot transactions will not drive housing prices up, but hot flipping areas will. The government should not be overly concerned about whether the housing market is hot or not but should pay attention to short-term flipping (repeated transactions within 2 years). In addition, the areas with low-priced houses are easily influenced by spatial aggregation of trading volume. Flipping detection and support measures should focus on areas with low housing prices, where they are more sensitively influenced by flipping transactions. Corresponding policies such as selective credit controls should refer to transaction (flipping) hotspot areas and set the optimal applicable areas of administrative districts.

Future research could explore more about the potential limitations of this study. First, this paper considers the hotspot effect through quantitative aggregation. However, if there is a significant urban–rural disparity in certain regions, areas with fewer residences are less likely to experience the emergence of hotspots. For instance, spot A mainly comprises low-density mansions, so there are few transactions, while spot B has many high-rise buildings and many transactions. However, the turnover rate of spot A, i.e., the ratio between the number of transactions relative to the number of housing units, is higher than that in spot B. It is an important issue to compare the nuanced difference between the quantity and the ratio concept. Fortunately, the urban characteristics of Taipei City, which has a relatively small geographical area and more balanced development, may mitigate such concerns. Second, the endogeneity of flipping activities is also an important consideration. For example, in a search-theoretic model of house flipping, as proposed by Leung and Tse (2017), flipping activities are considered endogenous. The relationships among housing prices, transactions, and flipping may exhibit multidirectional influences. Finally, it is worth noting that the transaction and flipping hotspots may change over time. Identifying the time-varying transaction and flipping hotspots could provide more practical implications. For future research, employing space-time permutation scan statistic methods (such as Kulldorff & Nagarwalla, 1995; Kulldorff et al., 2005) to analyze changes in clusters over time would be particularly suitable.

Acknowledgements

We would like to thank the Editors and three anonymous referees for providing highly constructive comments. The authors acknowledge the funding support received from the Chin-Oh Chang's Inheritance Award, Chinese Society of Housing Studies. Special appreciation is extended to Professor Chin-Oh Chang for his valuable and insightful comments on this paper. Chih-Yuan Yang extends thanks to the National Science and Technology Council of Taiwan for financial support through grant (NSTC 112-2410-H-003-131).

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Appendix

Table A1. Complete results of OLS model and spatial autoregression models

Model	OLS model		Spatial lag model		Spatial error model	
Variable	Coeff.	*t* value	Coeff.	Variable	Coeff.	Variable
Constant	16.149	1394.93***	16.184	1426.16***	16.224	1350.06***
Area	0.008	315.66***	0.008	316.60***	0.007	179.92***
Floor	–0.0004	–1.05	–0.0001	–0.37	–0.0008	–2.33**
TStory	–0.0003	–1.01	–0.0004	–1.33	–0.0009	–2.69***
Bathroom	0.059	24.31***	0.060	25.31***	0.061	25.42***
Age	–0.011	–118.36***	–0.011	–121.44***	–0.011	–114.10***
Dist. MRT	–0.011	–40.04***	–0.011	–39.90***	–0.011	–37.84***
Dist. CC	–0.004	–32.22***	–0.003	–27.49***	–0.003	–31.16***
THA	**–0.102**	**–34.74*** **	**–0.099**	**–34.56*** **	**–0.101**	**–34.42*** **
FHA	**0.014**	**1.08**	**0.022**	**1.70* **	**0.020**	**1.55**
THA × FHA	**0.042**	**1.68* **	**0.050**	**2.02** **	**0.032**	**1.30**
Administrative districts						
Zhongzheng	0.250	37.19***	0.174	25.94***	0.232	34.38***
Datong	0.036	5.26***	0.025	3.70***	0.034	4.83***
Zhongshan	0.119	22.63***	0.077	14.82***	0.102	19.26***
Songshan	0.300	46.97***	0.253	40.03***	0.284	44.32***
Da'an	0.395	58.62***	0.275	39.49***	0.361	52.55***
Xinyi	0.287	44.97***	0.209	32.59***	0.265	41.20***
Shilin	0.298	45.58***	0.235	36.03***	0.283	43.23***
Beitou	0.149	17.49***	0.102	12.14***	0.144	16.93***
Neihu	0.193	35.74***	0.133	24.65***	0.187	34.63***
Nangan	0.251	37.74***	0.160	23.70***	0.249	37.47***
Wensha	0.032	5.86***	0.016	3.06***	0.036	6.62***
Trading years × quarters						
2012Q3	–0.259	–24.86***	–0.260	–25.51***	–0.247	–23.76***
2012Q4	–0.243	–25.68***	–0.249	–26.90***	–0.231	–24.45***
2013Q1	–0.186	–18.83***	–0.190	–19.73***	–0.176	–17.95***
2013Q2	–0.130	–14.11***	–0.135	–15.00***	–0.123	–13.36***
2013Q3	–0.112	–11.56***	–0.118	–12.50***	–0.106	–11.04***
2013Q4	–0.093	–9.87***	–0.096	–10.40***	–0.087	–9.25***
2014Q1	–0.075	–7.49***	–0.077	–7.87***	–0.071	–7.09***
2014Q2	–0.131	–13.41***	–0.137	–14.37***	–0.122	–12.55***
2014Q3	–0.087	–8.60***	–0.092	–9.26***	–0.080	–7.88***
2014Q4	–0.089	–9.10***	–0.090	–9.35***	–0.086	–8.83***
2015Q1	–0.073	–6.71***	–0.074	–6.91***	–0.070	–6.46***
2015Q2	–0.059	–5.68***	–0.066	–6.54***	–0.054	–5.24***
2015Q3	–0.066	–6.16***	–0.068	–6.48***	–0.058	–5.43***
2015Q4	–0.095	–9.33***	–0.095	–9.54***	–0.087	–8.64***
2016Q1	–0.107	–8.92***	–0.109	–9.37***	–0.099	–8.36***
2016Q2	–0.064	–6.42***	–0.068	–6.93***	–0.058	–5.79***
2016Q3	–0.102	–9.38***	–0.104	–9.76***	–0.096	–8.83***
2016Q4	–0.107	–9.75***	–0.106	–9.83***	–0.100	–9.07***
2017Q1	–0.109	–9.48***	–0.107	–9.52***	–0.101	–8.81***
2017Q2	–0.093	–8.47***	–0.091	–8.50***	–0.084	–7.70***
2017Q3	–0.115	–10.39***	–0.116	–10.71***	–0.106	–9.59***
2017Q4	–0.130	–11.95***	–0.130	–12.19***	–0.121	–11.16***
2018Q1	–0.111	–9.63***	–0.108	–9.56***	–0.102	–8.93***
2018Q2	–0.123	–11.44***	–0.121	–11.55***	–0.115	–10.72***

End of Table A1

Model	OLS model		Spatial lag model		Spatial error model	
2018Q3	–0.104	–9.39***	–0.103	–9.47***	–0.097	–8.79***
2018Q4	–0.073	–6.65***	–0.075	–7.00***	–0.065	–5.98***
2019Q1	–0.086	–7.64***	–0.090	–8.15***	–0.079	–7.01***
2019Q2	–0.091	–8.62***	–0.092	–8.98***	–0.085	–8.10***
2019Q3	–0.082	–7.62***	–0.085	–8.03***	–0.077	–7.22***
2019Q4	–0.074	–7.03***	–0.075	–7.28***	–0.070	–6.71***
2020Q1	–0.071	–6.28***	–0.072	–6.54***	–0.065	–5.80***
2020Q2	–0.053	–5.06***	–0.054	–5.23***	–0.047	–4.50***
2020Q3	–0.036	–3.48***	–0.041	–4.13***	–0.032	–3.05***
2020Q4	–0.034	–3.28***	–0.039	–3.81***	–0.031	–2.99***
2021Q1	–0.019	–1.82**	–0.022	–2.09**	–0.018	–1.71*
2021Q2	–0.014	–1.30	–0.018	–1.65*	–0.013	–1.20
2021Q3	–0.014	–1.25	–0.017	–1.61	–0.012	–1.11
Spatial autocorr. coeff.	–		0.196	52.50***	0.056	22.32***
(Pseudo) *R*-square	0.852		0.859		0.855	
F value	6215.69***		–			
AIC	14781.55		14678.08			14737.21
Robust lag	–		683.37***			

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A2. Complete results of the spatial quantile regression model

Model	Low		.... Housing prices		....				High	
	0.1 q		0.25 q		0.5 q		0.75 q		0.9 q	
Variable	Coeff.	*t* value	Coeff.	*t* value	Coeff.	*t* value	Coeff.	*t* value	Coeff.	*t* value
Constant	15.916	582.66***	16.067	991.19***	16.155	1303.56***	16.236	1297.69***	16.334	1150.88***
Area	0.008	131.06***	0.008	230.96***	0.008	305.09***	0.008	300.55***	0.008	265.16***
Floor	–0.002	–2.15**	0.001	1.51	0.001	3.91***	0.002	5.064***	0.002	3.27***
TStory	–0.004	–5.40***	–0.001	–3.01***	0.001	3.31***	0.003	7.32***	0.003	6.37***
Bathroom	0.069	12.16***	0.061	17.98***	0.055	21.54***	0.054	20.79***	0.049	16.63***
Age	–0.012	–55.95***	–0.012	–88.20***	–0.011	–105.21***	–0.010	–100.58***	–0.010	–86.66***
Dist. MRT	–0.012	–17.80***	–0.013	–33.05***	–0.011	–38.23***	–0.010	–32.26***	–0.009	–25.01***
Dist. CC	–0.002	–9.48***	–0.003	–16.04***	–0.003	–26.20***	–0.004	–29.40***	–0.004	–26.04***
THA	**–0.122**	**–17.62*** **	**–0.124**	**–30.11*** **	**–0.097**	**–30.80*** **	**–0.061**	**–19.22*** **	**–0.038**	**–10.64*** **
FHA	**0.069**	**2.24** **	**0.050**	**2.74*** **	**0.014**	**1.69* **	**–0.018**	**–1.26**	**–0.024**	**–1.51**
THA × FHA	**–0.023**	**–0.40**	**0.037**	**1.07**	**0.056**	**2.10** **	**0.089**	**3.30*** **	**0.045**	**1.45**
Administrative districts										
Zhongzheng	0.227	14.01***	0.113	11.76***	0.130	17.66***	0.190	25.65***	0.226	26.85***
Datong	0.017	1.65*	–0.020	–2.11**	0.015	2.02**	0.038	5.06***	0.054	6.34***
Zhongshan	0.010	0.83	–0.016	–2.18**	0.078	13.67***	0.130	22.51***	0.170	26.03***
Songshan	0.280	18.37***	0.209	23.20***	0.227	32.81***	0.251	36.07***	0.270	34.13***
Da’an	0.282	16.76***	0.233	23.41***	0.253	33.15***	0.294	38.27***	0.326	37.37***
Xinyi	0.233	15.08***	0.159	17.36***	0.189	26.95***	0.229	32.37***	0.252	31.44***
Shilin	0.236	15.03***	0.170	18.28***	0.213	29.98***	0.272	37.88***	0.308	37.82***
Beitou	0.051	2.52**	0.013	1.08	0.102	11.11***	0.172	18.66***	0.199	18.95***
Neihu	0.186	14.31***	0.080	10.36***	0.101	17.17***	0.141	23.62***	0.163	24.13***
Nangan	0.236	14.52***	0.129	13.31***	0.143	19.40***	0.141	18.97***	0.118	14.04***
Wensha	0.070	5.46***	–0.027	–3.49***	–0.007	–1.20	0.017	2.85***	0.023	3.39***

End of Table A2

Model	Low		.... Housing prices						High	
	0.1 q		0.25 q		0.5 q		0.75 q		0.9 q	
Trading years × quarters										
2012Q3	–0.323	–13.15***	–0.269	–18.48***	–0.254	–22.80***	–0.220	–19.58***	–0.206	–16.19***
2012Q4	–0.294	–13.19***	–0.269	–20.35***	–0.243	–24.05***	–0.206	–20.19***	–0.200	–17.32***
2013Q1	–0.258	–11.09***	–0.220	–15.99***	–0.175	–16.64***	–0.155	–18.30***	–0.145	–12.03***
2013Q2	–0.185	–8.54***	–0.144	–11.17***	–0.120	–12.20***	–0.108	–10.83***	–0.108	–9.56***
2013Q3	–0.170	–7.46***	–0.133	–9.84***	–0.109	–10.61***	–0.087	–8.34***	–0.097	–8.19***
2013Q4	–0.144	–6.53***	–0.109	–8.33***	–0.086	–8.60***	–0.073	–7.16***	–0.073	–6.33***
2014Q1	–0.118	–5.01***	–0.086	–6.16***	–0.072	–6.75***	–0.061	–5.67***	–0.053	–4.30***
2014Q2	–0.325	–14.12***	–0.136	–9.93***	–0.091	–8.66***	–0.065	–6.13***	–0.059	–4.90***
2014Q3	–0.109	–4.55***	–0.103	–7.30***	–0.093	–8.63***	–0.062	–5.66***	–0.078	–6.29***
2014Q4	–0.111	–4.79***	–0.088	–6.38***	–0.068	–6.45***	–0.066	–6.26***	–0.069	–5.78***
2015Q1	–0.138	–5.37***	–0.107	–7.05***	–0.067	–11.89***	–0.041	–3.50***	–0.040	–3.06***
2015Q2	–0.098	–4.00***	–0.083	–5.71***	–0.054	–4.70***	–0.041	–3.65***	–0.058	–4.60***
2015Q3	–0.093	–3.68***	–0.076	–5.07***	–0.070	–6.36***	–0.066	–5.72***	–0.071	–5.39***
2015Q4	–0.132	–5.53***	–0.112	–7.88***	–0.103	–9.50***	–0.082	–7.44***	–0.081	–6.52***
2016Q1	–0.128	–4.54***	–0.117	–6.99***	–0.097	–7.63***	–0.096	–11.62***	–0.112	–7.68***
2016Q2	–0.096	–4.09***	–0.084	–6.00***	–0.077	–7.23***	–0.057	–5.26***	–0.057	–4.69***
2016Q3	–0.136	–5.29***	–0.125	–8.21***	–0.112	–9.65***	–0.082	–7.00***	–0.089	–6.68***
2016Q4	–0.129	–4.97***	–0.124	–8.06***	–0.116	–9.83***	–0.085	–7.17***	–0.086	–6.37***
2017Q1	–0.139	–5.12***	–0.122	–7.56***	–0.115	–9.31***	–0.105	–8.42***	–0.110	–7.82***
2017Q2	–0.109	–4.24***	–0.107	–7.02***	–0.104	–8.91***	–0.094	–7.96***	–0.084	–6.31***
2017Q3	–0.148	–5.66***	–0.120	–7.71***	–0.122	–10.32***	–0.115	–9.63***	–0.120	–8.86***
2017Q4	–0.158	–6.17***	–0.138	–9.05***	–0.135	–11.61***	–0.144	–12.26***	–0.122	–9.20***
2018Q1	–0.129	–4.78***	–0.109	–6.77***	–0.118	–9.60***	–0.111	–8.97***	–0.107	–7.58***
2018Q2	–0.153	–6.06***	–0.116	–7.75***	–0.123	–10.71***	–0.119	–10.31***	0.122	–9.32***
2018Q3	–0.114	–4.37***	–0.116	–7.46***	–0.112	–9.43***	–0.099	–8.31***	–0.089	–6.65***
2018Q4	–0.102	–3.96***	–0.093	–6.09***	–0.086	–7.34***	–0.059	–4.98***	–0.073	–5.45***
2019Q1	–0.086	–3.23***	–0.095	–6.01***	–0.097	–8.02***	–0.095	–7.83***	–0.108	–7.83***
2019Q2	–0.093	–3.73***	–0.077	–5.23***	–0.095	–8.42***	–0.098	–8.64***	–0.111	–8.66***
2019Q3	–0.100	–3.93***	–0.096	–6.35***	–0.093	–8.09***	–0.070	–6.04***	–0.087	–6.57***
2019Q4	–0.090	–3.63***	–0.070	–4.77***	–0.084	–7.50***	–0.067	–5.89***	–0.082	–6.34***
2020Q1	–0.069	–2.61***	–0.076	–4.83***	–0.077	–6.35***	–0.073	–5.96***	–0.092	–6.67***
2020Q2	–0.049	–1.97**	–0.054	–3.72***	–0.065	–5.80***	–0.060	–5.28***	–0.070	–5.48***
2020Q3	–0.039	–1.69*	–0.036	–2.53**	–0.052	–4.72***	–0.051	–4.60***	–0.067	–5.33***
2020Q4	–0.036	–1.48	–0.041	–2.88***	–0.035	–3.19***	–0.038	–3.46***	–0.047	–3.77***
2021Q1	–0.033	–1.31	–0.020	–1.35	–0.023	–2.04**	–0.015	–1.34	–0.026	–1.99**
2021Q2	–0.029	–1.14	–0.022	–1.43	–0.022	–1.84*	–0.014	–1.16	–0.030	–2.21**
2021Q3	–0.017	–0.67	–0.015	–0.97	–0.018	–1.55	–0.016	–1.39	–0.036	–2.67***
Spatial autocorr. coeff.	0.163	18.14***	0.185	34.70***	0.200	48.77***	0.214	51.82***	0.217	46.49***
(Pseudo) *R*-square	0.577		0.606		0.641		0.671		0.693	