

# THE IMPACT OF A MASS RAPID TRANSIT SYSTEM ON NEIGHBORHOOD HOUSING PRICES: AN APPLICATION OF DIFFERENCE-IN-DIFFERENCE AND SPATIAL ECONOMETRICS

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## Abstract

This study discusses the impact of the mass rapid transit (MRT) system's construction and operation on neighborhood housing prices. Estimations were conducted by considering the spatial dependence of housing prices and using a difference-in-difference (DD) method that incorporated the spatial lag model and spatial error model. The empirical results indicated that the coefficient of the interaction variable of the MRT's range of influence and commencement time of construction was -0.079, reaching the 10% significance level. Hence, when MRT construction began, housing prices in the experimental group decreased by 7.9% as compared to the control group. A possible reason for these findings is that the "dark age" of urban traffic, air pollution, and noise brought about by MRT construction negatively affected housing prices. With regard to MRT operations, the coefficient of the interaction variable of the MRT's influence range and service commencement time did not reach the level of significance, indicating that housing prices within the MRT's influence range were not significantly affected when the MRT's service began. This might be due to the fact that the psychological expectations of the increase in housing prices had already been realized during the planning, announcement, and construction phases.

**Key words:** *housing prices; mass rapid transit, geographic information system, difference-in-difference, spatial error model, spatial lag model.*

**JEL Classification:** C21, O18, P25.

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## 1. Introduction

Mass rapid transit (MRT) systems are an important means of transportation in Taiwan. For instance, the Taipei Metro, the MRT system with the longest operating history in Taiwan, has solved the issue of traffic congestion in the metropolitan area. The Taipei Metro launched its services in 1996 and has

been operating for over 20 years. The metro consists of five lines, namely: the Wenhua, Tamsui-Xinyi, Songshan-Xindian, Zhonghe-Xinlu, and Bannan lines, and 117 stations. The MRT system has partially alleviated traffic issues, increased commuting convenience, and promoted the rise of neighborhood housing prices.

Studies by Dziauddin et al. (2013) and Ryan (2005) indicated an increase in housing prices near the metro and light rail stations. Bowes and Ihlanfeldt (2001) also maintained that metro stations can cause an increase in neighborhood housing prices. McMillen and McDonald (2004) studied the effect of a MRT line from downtown Chicago to Midway Airport on neighboring housing prices before and after the line opened. The empirical results showed that housing prices were already affected in the 1980s and early 1990s, prior to the opening of the line. This indicates that housing prices are affected by the anticipated construction of a MRT. Between 1986 to 1999, housing prices within 1.5 miles of the line increased by US\$216 million. Yiu and Wong (2005) analyzed the impact of the MRT system on neighborhood housing prices using a hedonic price model and found that the construction of transport had a significant positive influence on neighborhood housing prices. The increased accessibility of MRT reduces commute time, making it an incentive to purchase housing near MRT stations. Agostini, Palmucci (2008) and Ge et al. (2012) suggested that announcements regarding the commencement and completion of transport system construction, as well as its launching, had a different effect on housing prices. Bowes and Ihlanfeldt (2001) and Boymal et al. (2013) analyzed the influence of transportation facilities on neighborhood housing prices and found that MRT stations had a significant positive effect on neighborhood housing prices. Wen, Gui, et al. (2018) suggested that the ordinary least squares (OLS) regression model can only estimate the mean implicit prices of housing characteristics and may ignore the various effects of mass transit systems on different housing prices. On the other hand, quantile regression can explain how changes in the implicit prices of housing attributes are affected by changes in housing prices. They used housing prices in Hangzhou, China, and adopted the OLS model and quantile regression model approaches to measure the capitalization effects of mass transit systems on housing prices. The empirical results showed that the housing prices of units located within 2 km of an MRT station were 2.1% to 6.1% higher than the prices of those located outside the 2 km range. The estimated coefficient increased from 0.023 in the 0.15 quantile to 0.086 in the 0.95 quantile. Therefore, mass transit systems will increase the capitalization effect of transport accessibility.

Billings (2011) and Dubé et al. (2013) investigated the impact of transportation facilities on neighborhood prices before and after policy announcements, at the beginning of construction, and at the beginning of service. This study suggested that MRT affects housing prices during both the construction and operation phases. Both phases were examined in order to explore the differences in the effects of MRT on neighborhood housing prices at different stages of operation.

According to Tobler's (1970) first law of geography, all objects are inter-related and their correlation increases with proximity. The housing-housing relationship can be affected by neighborhood housing prices. Dubin (1998) indicated that housing prices can be predicted by establishing a hedonic regression based on housing characteristics and employing the ordinary least squares (OLS) method as a statistical tool. However, this method ignores the issue of the spatial correlation between neighborhood housing prices. A study by Chen and Haynes (2015) confirmed the presence of spatial dependence in housing prices. The failure to solve the issue of spatial dependence can cause bias in coefficient estimations. Diao, Leonard and Sing (2017) utilized Singapore's new Circle Line (CCL) as a natural experiment and used the spatial differences-in-differences approach to examine the effects of network distance on non-landed housing prices. The empirical results showed that the opening of the CCL will increase housing prices in the experimental zone (within a 600-meter range of CCL stations) by 8.6%, approximately S\$380.12 million, relative to the control zone after controlling for heterogeneities in housing attributes, nearby facilities and spatial and temporal fixed effects. The results of estimations are rendered more accurate by using the shortest network distance measure for assessment, while the Euclidean distance measure will decrease the estimated coefficient. There were anticipation effects one year prior to the opening of the CCL line, but these effects gradually diminished with time. Housing prices were mostly affected during Phase 2 and Phase 3 of the opening of the MRT line. Spatial dependence was observed in housing in the experimental and control zones, and such a dependence will cause errors in estimations if neglected. Kopczewska and Lewandowska (2018) utilized spatial modelling to measure the spatial econometrics and location

effects of office rental rates. Their empirical results indicate that geographical factors increased office rental rates by about 50%, and the rates increased by about 0.7 pounds per square foot for every 100 feet closer to an MRT station, while rental rates in the city center increased by 20 pounds per square foot in the same manner. Trojanek and Gluszak (2018) used the ordinary least squares approach (OLS), spatial autoregressive model (SAR), spatial error model (SEM) and spatial general model (SGM) integrated with the differences-in-differences (DID) approach to investigate the effect of MRT lines on housing prices. They discovered that the housing prices were already affected prior to the opening of the MRT. This study considered the possible effect of neighborhood housing prices on housing prices. Housing prices near an area with high housing prices are likely to be high, whereas housing prices near an area with low housing prices are likely to be low. In addition to the difference-in-difference (DD) method, this study also integrated spatial econometrics. A spatial econometric model was applied to explore the influence of neighborhood housing prices on housing prices and to reduce the potential bias of the traditional regression model.

The Xinyi line of the Taipei Metro was examined in this study. The construction of the Xinyi line began in 2005, and it was put into service on November 24, 2013, making it the second Taipei Metro line to operate in the east-west direction. This study employed the DD method. The start of the construction was set as the dividing time point and metro operation was designated as the influencing event to examine the influence of metro construction and operation on neighborhood housing prices. Furthermore, spatial dependence between housing prices, which is ignored in the traditional regression model, was considered. Thus, in addition to the DD method, a spatial econometric model was used in the analyses. The objectives of this study were to explore (1) the changes in housing prices within the MRT range of influence after the beginning of metro construction and operation, as well as the differences with respect to the influence of MRT construction time and operation time on housing prices within the specified influence range, and (2) the spatial autocorrelation between neighborhood housing prices and the influence of neighborhood housing prices on housing prices.

## 2. Methods

### 2.1. Empirical Model Establishment

The DD method is applied to evaluate differences in influence before and after an event or policy implementation. Therefore, the affected group was set as the experimental group and the non-affected group was set as the control group. The experimental and control groups were further divided into the control group before the policy/event, experimental group before the policy/event, control group after the policy/event, and experimental group after the policy/event, and differences between the groups were analyzed. In this study, two policies were evaluated. The beginning of metro construction and beginning of metro operation were set as the events that influenced neighborhood housing prices; changes before and after these events were measured. Areas within the metro influence range were included in the experimental group, and areas outside this range were included in the control group. A DD model was established and used as the basis for the spatial lag model and spatial error model used in the analyses.

First, the independent variables related to housing characteristics that could affect housing prices included the age of the building ( $AGE$ ), the age of the building squared ( $AGE^2$ ), the number of rooms ( $ROOM$ ), the number of living rooms ( $LIVROOM$ ), number of bathrooms ( $BATH$ ), housing type ( $TYPE$ ), location on the first floor ( $FLOOR1$ ), and location on the fourth floor ( $FLOOR4$ ). Variables in the DD method included metro influence time ( $TIME_t$ ), metro influence range ( $MRT_t$ ), and metro influence range  $\times$  metro influence time ( $MRT_t \times TIME_t$ ). The DD model was established as shown in Equation (1):

$$\ln P_{it} = \beta_1 + \beta_2 AGE_{it} + \beta_3 AGE_{it}^2 + \beta_4 ROOM_{it} + \beta_5 LIVROOM_{it} + \beta_6 BATH_{it} + \beta_7 TYPE_{it} + \beta_8 FLOOR1_{it} + \beta_9 FLOOR4_{it} + \beta_{10} TIME_t + \beta_{11} MRT_t + \delta(TIME_t \times MRT_t) + e_{it} \quad (1)$$

where  $\beta_1$  is the intercept;  $\beta_2 \sim \beta_9$  are coefficients of structural characteristics of housing; and  $\beta_{10}$ ,  $\beta_{11}$ , and  $\delta$  are coefficients of metro influence time, metro influence range, and the interaction of

metro influence time and metro influence range, respectively.  $e_{it}$  is the normally distributed error term. The equation was evaluated using OLS.

Second, a spatial lag model was established based on the DD model, as shown in equation (2):

$$\ln P_{it} = \alpha_1 + \rho W(\ln P_{it}) + \alpha_2 AGE_{it} + \alpha_3 AGE_{it}^2 + \alpha_4 ROOM_{it} + \alpha_5 LIVROOM_{it} + \alpha_6 BATH_{it} + \alpha_7 TYPE_{it} + \alpha_8 FLOOR1_{it} + \alpha_9 FLOOR4_{it} + \alpha_{10} TIME_t + \alpha_{11} MRT_i + \delta(TIME_t \times MRT_i) + \varepsilon_{it} \quad (2)$$

where  $\alpha_1$  is the intercept;  $\alpha_2 \sim \alpha_9$  are coefficients of the structural characteristics of housing; and  $\alpha_{10}$ ,  $\alpha_{11}$ , and  $\delta$  are coefficients of metro influence time, metro influence range, and the interaction of metro influence time and metro influence range, respectively.  $W(\ln P_{it})$  is the explained variable multiplied by the spatial weights matrix  $W$ .  $\rho$  is the spatial lag coefficient.  $e_{it}$  is the error term.  $\rho \neq 0$  indicated spatial autocorrelation between neighborhood housing prices.

Third, a spatial error model was established based on the DD model, as shown in Equation (3):

$$\ln P_{it} = \theta_1 + \theta_2 AGE_{it} + \theta_3 AGE_{it}^2 + \theta_4 ROOM_{it} + \theta_5 LIVROOM_{it} + \theta_6 BATH_{it} + \theta_7 TYPE_{it} + \theta_8 FLOOR1_{it} + \theta_9 FLOOR4_{it} + \theta_{10} TIME_t + \theta_{11} MRT_i + \delta(TIME_t \times MRT_i) + \gamma_{it} \quad (3)$$

where  $\theta_1$  is the intercept;  $\theta_2 \sim \theta_9$  are coefficients of structural characteristics of housing; and  $\theta_{10}$ ,  $\theta_{11}$ , and  $\delta$  are coefficients of metro influence time, metro influence range, and the interaction of metro influence time and metro influence range, respectively.  $\gamma_{it}$  is the error term. The error term after correction was as shown in Equation (4):

$$\gamma_{it} = \lambda W\gamma_{it} + \xi, \quad \xi \sim N(0, \sigma^2) \quad (4)$$

$\lambda$  is the spatial error coefficient.  $\lambda \neq 0$  indicated spatial correlation in the spatial error regression model due to confounding factors (ANSELIN 1988).

## 2.2. Establishment and Explanation of Variables

The dependent variable in this study was the logarithm of the total real estate transaction price. Independent variables in this study included the age of the building ( $AGE_{it}$ ), the age of the building squared ( $AGE_{it}^2$ ), the number of rooms ( $ROOM_{it}$ ), number of living rooms ( $LIVROOM_{it}$ ), the number of bathrooms ( $BATH_{it}$ ), location on the first floor ( $FLOOR1_{it}$ ), location on the fourth floor ( $FLOOR4_{it}$ ), and housing type ( $TYPE_{it}$ ). Coefficients of the number of rooms ( $ROOM_{it}$ ), number of living rooms ( $LIVROOM_{it}$ ), and number of bathrooms ( $BATH_{it}$ ) were expected to be positive values.

The variable related to the beginning of metro construction and operation ( $TIME_t$ ) was established as follows. With regard to the beginning of construction, the transaction data sample was collected from January 2004 to December 2006, and the year 2005 was set as the time point when construction of the Xinyi line began. Data prior to and after the beginning of construction was coded as 0 and 1, respectively. With regard to the commencement of operation, the data sample was collected from January 2011 to December 2014. November 2013 was set as the time point when the Xinyi line was introduced into service. Data prior to and after the beginning of operation was coded as 0 and 1, respectively.

With regard to the metro station influence range, Gibbons and Machin (2005) evaluated housing prices within 1.25 miles from stations in London. Cervero and Duncan (2002) explored the impact of the California Santa Clara light rail and commuter rail on neighborhood housing prices by setting 1/4 mile (approximately 400 meters) as the influence range. In a study by Armstrong and Rodriguez (2006), housing prices within 1/2 mile from a station were 10.1% higher than those outside this range. Dewees (1976) set 1/3 mile (approximately 500 meters) as the range of stations' influence on housing

prices. Taiwanese scholars Feng, Tseng and Wang (1994) included areas within 500 meters from each MRT station in the influence range, which was further subdivided for the metropolitan zone (0-100 meters), marginal zone (100-300 meters), and suburban zone (300-500 meters). According to the MRT line planning principles published on the website of the Department of Rapid Transit Systems, Taipei City Government, distance between stations should be maintained within 800-1000 meters in city center areas and 1000-2000 meters in suburban areas as part of the road network plan. Moreover, in order to ensure MRT accessibility, distance between stations should not exceed 2400 meters. This study considered walking distance and the fact that MRT stations' influence ranges should not overlap. Therefore, a 500-meter distance from an MRT station was established as the main research range using GIS. Housing units within the 500-meter influence range were included in the experimental group, and housing units outside the influence range were included in the control group. With regard to the metro station influence range ( $MRT_i$ ) variable, data within the 500-meter influence range of MRT stations was coded as 1 and data outside this range was coded as 0.

The interaction variable of the beginning of metro construction and operation and metro station influence range ( $TIME_i * MRT_i$ ) referred to the location within the influence range after the beginning of metro construction and operation. Due to environmental pollution caused by the produced dust and the "dark age" of traffic caused by traffic inconvenience, the coefficient related to the location within the influence range after the beginning of construction was predicted to be negative. The coefficient related to the location within the influence range after the beginning of operation was predicted to be positive. Coefficients related to this variable were DD coefficients (Table 1).

**Table 1**

#### Definition of variables

Variable	Definition	Expected Sign
$\ln P_{it}$	Logarithm of the total price of housing (incl. objects) transaction.	
$AGE_{it}$	Based on the difference between the date of building construction completion and the date of transaction, measured in years.	—
$AGE_{it}^2$	Based on the difference between the date of building construction completion and the date of transaction and squared, measured in years.	+
$ROOM_{it}$	Number of rooms in the building.	+
$LIVROOM_{it}$	Number of living rooms in the building.	+
$BATH_{it}$	Number of bathrooms in the building.	+
$FLOOR1_{it}$	Location on the first floor was set as a dummy variable, with 1 indicating the first floor and 0 indicating other floors. The first floor can be used for shops and has a commercial value. Therefore, housing prices were predicted to be high.	+
$FLOOR4_{it}$	Location on the fourth floor was set as a dummy variable, with 1 indicating the fourth floor and 0 indicating other floors. In Mandarin, the pronunciation of "four" resembles that of "death" and, therefore, there is a bias towards the fourth floor. Thus, the prices of housing on the fourth floor were predicted to be low.	—
$TYPE_{it}$	Housing types included apartment buildings, multistoried residential buildings, and mansions. The housing type was set as a dummy variable, with 1 indicating multistoried buildings and mansions and 0 indicating apartment buildings.	+
$TIME_i$	With regard to the beginning of construction, the transaction data sample was collected from January 2004 to December 2006, and the year 2005 was set as the time point when construction of the Xinyi line began. Data prior to and after the beginning of construction was coded as 0 and 1, respectively. With regard to the beginning of	+



	operation, the data sample was collected from January 2011 to December 2014. November 2013 was set as the time point when the Xinyi line was introduced into service. Data prior to and after the beginning of operation was coded as 0 and 1, respectively.	
$MRT_i$	This study considered walking distance and the fact that MRT stations' influence ranges should not overlap. Therefore, a 500-meter distance from an MRT station was established as the main research range. Housing units within the 500-meter influence range were coded as 1 and housing units outside the influence range were coded as 0.	+
$MRT_i \times TIME_t$	Due to environmental pollution caused by the produced dust and the "dark age" of traffic caused by traffic inconvenience, the coefficient related to the location within the influence range after the beginning of construction was predicted to be negative. The coefficient related to the location within the influence range after the commencement of operation was predicted to be positive. Coefficients related to this variable were DD coefficients.	+/-

Source: own study.

### 3. Data Collection and Sample Statistics

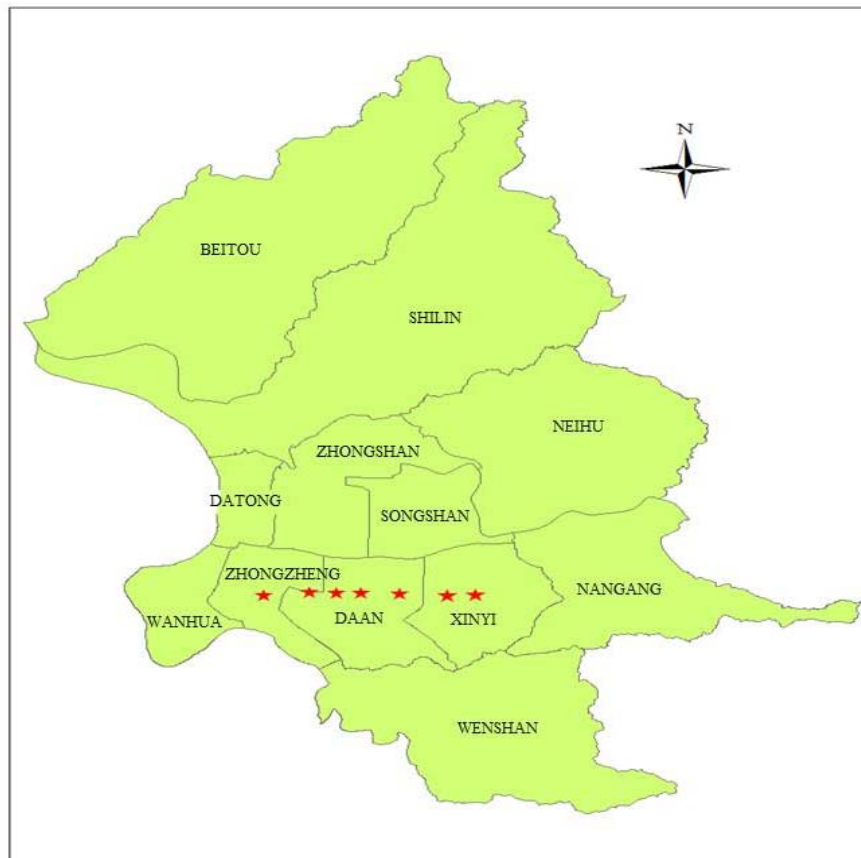
#### 3.1. Data Source Explanation

Housing transaction data in this study was obtained from the reports on Taiwan real estate transactions published by the Department of Land Administration of the Ministry of the Interior and GigaHouse. Taipei City was set as the research range, with the main research areas including the Da'An District, Zhongzheng District, and Xinyi District, which are connected by the Xinyi line. The influence of metropolitan transport on neighborhood housing prices after the beginning of its construction and operation was explored using the example of the Taipei Metro Xinyi line. With regard to the beginning of metro construction, the Xinyi line project tendering began in April 2005, with its construction beginning July 2005. Thus, the year 2005 was set as the construction commencement time in this study. Statistical analysis was conducted using 2004 and 2006 housing transaction data. In total, 2,315 transactions were analyzed after the exclusion of data with missing values and special transactions. With regard to the beginning of metro operation, to ensure sufficiency of data, housing transaction data from 2011-2014 was collected. The opening of the Xinyi line in November 2013 was set as the basis and data related to housing transactions made within one month before and after the opening was excluded. Thus, statistical analysis included data from January 2011 to September 2013 and from January to December 2014. With respect to the metro's opening, due to the lack of data, housing transaction data from 2011 to 2014 were collected instead, and the time point was set at November 2013, that is, the year the Xinyi Line opened. In total, 2,266 transactions were analyzed after exclusion of data with missing values and special transactions.

According to the website of the Department of Rapid Transit Systems, Taipei City Government, the Xinyi line runs from Chiang Kai-shek Memorial Hall MRT station along Xinyi Road to the Xinyi Planning District, crossing Jinhua Street, Aiguo East Road, and Hangzhou South Road and ending in Xiangshan Park. The line spans 6.4 km with seven underground stations, including Xiangshan Station, Taipei 101/World Trade Center Station, Xinyi Anhe Station, Daan Station, Daan Park Station, and Chiang Kai-shek Memorial Hall Station. The entire line was constructed underground (Figure 1).

#### 3.2. Sample Statistics

Table 2 provides statistics for the transaction data sample related to the beginning of metro construction.



Stars indicate stations

**Fig. 1.** Taipei Metro Xinyi Line route map. *Source:* own study.

**Table 2**

Sample statistics: Beginning of construction as the division time point (N=2,315)

Variable	Mean	SD	Max.	Min.	Unit of Measurement
<i>PRICE</i>	1103.53	560.330	6800	135	NT\$10,000
<i>AGE</i>	23.00	8.992	43	0	Years
<i>TYPE</i>	0.60	-	1	0	-
<i>ROOM</i>	2.79	0.894	5	1	Rooms
<i>LIVROOM</i>	1.85	0.384	3	1	Rooms
<i>BATH</i>	1.58	0.493	2	1	Rooms
<i>FLOOR</i>	0.06	-	1	0	-
<i>FLOOR4</i>	0.21	-	1	0	-

Source: own study.

Table 3 provides statistics for the transaction data sample related to the beginning of metro operation.

**Table 3**

Sample statistics: Beginning of operation as the division time point (N=2,266)

Variable	Mean	SD	Max.	Min.	Unit of Measurement
<i>PRICE</i>	2378.37	1442.626	33,300	410	NT\$10,000
<i>AGE</i>	23.78	10.293	48	0	Years
<i>TYPE</i>	0.72	-	1	0	-
<i>ROOM</i>	2.70	0.960	9	1	Rooms
<i>LIVROOM</i>	1.80	0.460	6	1	Rooms
<i>BATH</i>	1.62	0.574	7	1	Rooms
<i>FLOOR1</i>	0.06	-	1	0	-
<i>FLOOR4</i>	0.16	-	1	0	-

Source: own study.

#### 4. Empirical Results

Spatial dependence was tested first. In this study, global spatial autocorrelation coefficients were used in the spatial econometric model to measure spatial autocorrelation. The calculation of global spatial autocorrelation requires that the spatial neighborhood within the research range be defined. Autocorrelation coefficients are derived from the spatial weights matrix. In this study, queen contiguity was set as the contiguity weight to examine whether spatial aggregation was present in housing prices. Moran's I reached the 1% significance level at the beginning of metro construction, indicating the presence of autocorrelation between neighborhood housing prices. The presence of aggregation needed to be tested using spatial models. LM-lag and LM-error values reached the 1% significance level. The robust LM-lag value was 56.325, reaching the 5% significance level. The robust LM-error value was 2.422, not reaching the significance level. With regard to metro operation, Moran's I was 0.2551, reaching the 1% significance level and indicating positive autocorrelation between housing prices. The presence of aggregation needed to be tested using spatial models. LM-lag and LM-error values reached the 1% significance level. The robust LM-lag value was 56.851, reaching the 1% significance level. The robust LM-error value was 29.149, reaching the 1% significance level. The results indicated the presence of autocorrelation between neighborhood housing prices and error terms.

This study compared calculations based on OLS, the spatial lag model, and the spatial error model. Regression analyses are provided in Table 4. The Breusch-Pagan test was performed to test the three models for residual heterogeneity; the results related to the beginning of metro construction reached the 1% significance level, indicating rejection of the heterogeneity null hypothesis in all three models and, thus, indicating the presence of residual heterogeneity in the regression models. The  $R^2$  values of the three models were 0.389, 0.434, and 0.431, respectively. The spatial lag model was found to explain most variance. Log likelihood, AIC, and SC values were used to indicate the goodness of fit of model estimation results. Higher log likelihood values were associated with lower AIC and SC coefficients and better goodness of fit. Log likelihood values of the models were -1338.05, -1270.2, and -1280.709, respectively. AIC values of the models



were 2700.1, 2566.41, and 2585.42, respectively. SC values of the models were 2769.06, 2641.12, and 2654.38, respectively. The results indicated that the spatial lag model had the best goodness of fit. Breusch-Pagan results related to the beginning of metro construction reached the 1% significance level, indicating rejection of the heterogeneity null hypothesis in all three models and, thus, indicating the presence of residual heterogeneity in the regression models. The  $R^2$  values of the three models were 0.357, 0.475, and 0.480, respectively. The spatial error model was found to explain most of the variance. With regard to the goodness of fit results, log likelihood values of the models were -1495.16, -1311.98, and -1316.54, respectively. AIC values of the models were 3014.32, 2649.96, and 2657.08, respectively. SC values of the models were 3083.03, 2724.39, and 2725.79, respectively. The results indicated that the spatial error model had the best goodness of fit.

The spatial lag and error model results are described here. With regard to housing structural characteristics when the beginning of metro construction was set as the division time point, the age of building coefficient was -0.023, reaching the 1% significance level. The coefficient of the age of the building squared was 0.001, reaching the 1% significance level. These results indicated that an older age of building was associated with lower housing prices; the rate of such a decrease in prices was smaller for older buildings. Coefficients of the number of rooms were 0.196 and 0.200, reaching the 1% significance level, which indicated that the housing price increased by 19.6% and 20.0% with each additional room, respectively. Coefficients of the number of living rooms were 0.212 and 0.217, reaching the 1% significance level, which indicated that the housing price increased by 21.2% and 21.7% with each additional living room, respectively. Coefficients of the number of bathrooms were 0.218 and 0.214, reaching the 1% significance level, which indicated that the housing price increased by 21.8% and 21.4% with each additional bathroom, respectively. The housing type coefficients were 0.217 and 0.194, reaching the 1% significance level, which indicated that housing prices in multistoried buildings and mansions were 21.7% and 19.4% higher than those in apartment buildings. The coefficients of the location on the first floor were 0.177 and 0.176, reaching the 1% significance level, which indicated that prices of housing units located on the first floor were 17.7% and 17.6% higher than those of housing units on other floors. Coefficients of the location on the fourth floor were -0.012 and -0.008, indicating a negative effect but not reaching the significance level. With regard to housing structural characteristics, when the commencement of metro operation was set as the division time point, the obtained coefficients were similar to those related to the beginning of metro construction in terms of direction and significance and, thus, are not discussed here.

With regard to DD variables, the coefficient of MRT construction commencement time was 0.229, reaching the 1% significance level. The results indicated that regardless of the distance between housing units and metro stations, housing prices increased by 22.9% after the beginning of metro construction. Coefficients of the MRT influence range were 0.114 and 0.165, reaching the 1% significance level. The results indicated that when the time of the beginning of metro construction was not considered, housing prices within the MRT influence range were 11.4% and 16.5% higher than those outside this range.

Coefficients of the interaction variable of the construction commencement time and the metro influence range were -0.079 and -0.091, reaching the 10% and 5% significance levels, respectively. These results indicated that after the commencement of metro construction, housing prices within the metro influence range (experimental group) decreased by 7.9% and 9.1% as compared to those outside the metro influence range (control group).

The coefficients of the metro operation beginning time were 0.104 and 0.129, reaching the 1% significance level, which indicated that, regardless of the distance between housing units and metro stations, housing prices after the beginning of metro operation were 10.4% and 12.9% higher than those before the beginning of metro operation. The coefficients of the metro influence range were 0.087 and 0.137, reaching the 1% significance level, which indicated that, when the time of the beginning of metro operation was not considered, housing prices within the metro influence range were 8.7% and 13.7% higher than those outside this range. The coefficients of the interaction variable of operation beginning time and the metro influence range were 0.003 and 0.010, indicating a positive effect but not reaching the significance level. The results indicated that there was no significant difference between housing prices within and outside the metro influence range after the beginning of metro operation.

With regard to spatial econometric models, spatial lag coefficients ( $\rho$ ) in the 500-meter spatial lag model were 0.373 and 0.474, reaching the 1% significance level, which indicated that housing prices were affected by neighborhood housing prices. Spatial error coefficients ( $\lambda$ ) in the spatial error model

were 0.434 and 0.539, reaching the 1% significance level, which indicated spatial autocorrelation between error terms due to confounding factors.

Table 4

## Analysis of empirical results

Variables	Construction			Operation		
	OLS	SLM	SEM	OLS	SLM	SEM
Independent variable	Coefficient (t value)	Coefficient t (t value)	Coefficient t (t value)	Coefficient (t value)	Coefficient t (t value)	Coefficient (t value)
Intercept	5.479*** (91.267)	3.019*** (13.457)	5.599*** (89.921)	6.414*** (125.893)	2.986*** (16.864)	6.592*** (123.763)
<i>AGE</i>	-0.023*** (-6.232)	-0.023*** (-6.439)	-0.023*** (-6.000)	-0.010*** (-2.648)	-0.013*** (-3.955)	-0.010*** (-2.738)
<i>AGE</i> <sup>2</sup>	0.001*** (5.486)	0.001*** (5.154)	0.001*** (4.482)	0.001 (1.525)	0.001** (2.058)	0.001 (0.930)
ROOM	0.199*** (14.805)	0.196*** (15.134)	0.200*** (15.280)	0.210*** (14.056)	0.201*** (14.921)	0.203*** (15.169)
LIVROOM	0.213*** (7.629)	0.212*** (7.861)	0.217*** (8.041)	0.138*** (5.034)	0.131*** (5.262)	0.141*** (5.747)
<i>BATH</i>	0.235*** (10.020)	0.218*** (9.633)	0.214*** (9.367)	0.225*** (9.631)	0.196*** (9.293)	0.193*** (9.117)
<i>TYPE</i>	0.273*** (12.315)	0.217*** (10.072)	0.194*** (8.309)	0.222*** (9.809)	0.148*** (7.211)	0.109*** (4.977)
<i>FLOOR</i>	0.164*** (4.283)	0.177*** (4.820)	0.176*** (4.820)	0.068* (1.662)	0.097*** (2.639)	0.129*** (3.556)
FLOOR4	-0.017 (-0.731)	-0.012 (-0.548)	-0.008 (-0.360)	-0.064** (-2.346)	-0.054** (-2.171)	-0.052** (-2.144)
<i>TIME</i> <sub><i>t</i></sub>	0.237*** (11.127)	0.229*** (11.143)	0.229*** (11.090)	0.094*** (3.528)	0.104*** (4.324)	0.129*** (5.415)
<i>MRT</i> <sub><i>i</i></sub>	0.174*** (5.109)	0.114*** (3.439)	0.165*** (3.942)	0.170*** (6.141)	0.087*** (3.450)	0.137*** (3.327)
<i>TIME</i> <sub><i>t</i></sub> × <i>MRT</i> <sub><i>i</i></sub>	-0.077* (-1.709)	-0.079* (-1.815)	-0.091** (-2.073)	0.005 (0.080)	0.003 (0.048)	0.010 (0.180)
Spatial Lag( $\rho$ )	-	0.373*** (11.451)	-	-	0.474*** (20.014)	-
Lambda( $\lambda$ )	-	-	0.434*** (11.515)	-	-	0.539*** (20.477)
Breusch-Pagan	50.167***	49.595***	49.833***	82.310***	37.050***	48.428***
Log likelihood	-1338.05***	-1270.2***	-1280.709***	-1495.16***	-1311.98***	-1316.538***
SC	2769.06	2641.12	2654.38	3083.03	2724.39	2725.79
AIC	2700.1	2566.41	2585.42	3014.32	2649.96	2657.08
<i>R</i> <sup>2</sup>	0.389	0.434	0.431	0.357	0.475	0.480

Note: \*\*\*, \*\*, and \* indicate that the coefficient reaches the 1%, 5%, and 10% significance level, respectively, and is significantly different from 0. Coefficient values are not standardized.

Source: own study.

## 5. Conclusion and Suggestions

This study explored one type of YIMBY facilities, namely, metro stations. The metro had different influences on housing prices at the beginning of construction, completion of construction, and beginning of operation (GE et al., 2012). The metro influence time points in this study included the commencement of construction and commencement of operation. The empirical results demonstrated that MRT had a different influence on neighborhood housing prices in these two phases.

This study considered the issue of potential spatial dependence between housing prices, which may be ignored in the OLS model. As failure to solve the issue of spatial dependence can cause bias in model estimation coefficients (CHEN HAYNES, 2015), this study used spatial econometric models to solve the issue. Prior to the empirical analyses, Moran's I was used to test spatial correlation within the research range in order to verify whether there was spatial autocorrelation between housing prices in Taipei. Moran's I was equal to 0.214 for the commencement of metro construction and 0.290 for the commencement of metro operation, reaching the 1% significance level. The results indicated the presence of positive spatial autocorrelation between housing prices in Taipei, as well as their aggregation.

The empirical results of the spatial lag model showed that the DD coefficient of the 500-meter influence range in the beginning of metro construction was -0.079, reaching the 10% significance level. The results indicated that housing prices within the 500-meter influence range decreased by 7.9% after the beginning of metro construction. Traffic inconveniences, due to metro construction and environmental externalities caused by dust from construction work had a negative effect on neighborhood housing prices. With regard to related studies, GE et al. (2012) found that the beginning of metro station construction had a significant negative effect on housing prices. SU (2011) and YANG (2007) suggested that environmental externalities, noise issue, congestion issue, and the "dark age" of traffic caused by metro construction can negatively affect housing prices. GENG et al. (2015) found that THSR stations negatively affected housing prices within the specified range, potential reasons for which were traffic jams, electromagnetic radiation pollution, noise, and crime rates near THSR stations.

With regard to metro operation, DD coefficients of the 500-meter influence range were 0.003 and 0.058, indicating positive but insignificant effects. The results showed that metropolitan transport did not significantly affect housing prices within the 500-meter influence range after the beginning of its operation. These results could be related to the "dark age" of traffic and noise caused by metro construction. Furthermore, this could follow the overreaction to the announcement of metro station construction. Due to the need for testing and governmental approval of the line, the Xinyi line was introduced into service only three years after completion of its construction. This study suggested that psychological anticipation could lead to the growth of neighborhood housing prices after completion of metro construction and prior to the official beginning of metro operation. McDONALD and OSUJI (1995) found that land prices increased prior to metro operation due to psychological anticipation. According to the empirical findings reported by BAE et al. (2003), metropolitan transport already had a significant effect on housing prices even before the beginning of its service. FERGUSON, GOLDBERG and MARK (1988) indicated that urban transit influenced the real estate market and housing prices before system operations began, which was due to psychological anticipation.

The announcement, construction, and introduction of a metro line into service usually take several years. This study was limited to exploring the influence of metro stations on neighborhood housing prices after the commencement of metro construction and after the commencement of metro operation. The effects of the metro stations on neighborhood housing prices in the planning, announcement, and construction completion phases were not discussed. Moreover, data used in this study only included housing transactions. Therefore, the influence of the Xinyi line on prices of other real estate types, for example, commercial real estate, was not explored. With regard to the influence range definition, it is suggested that future studies apply different distances when determining the experimental group in order to analyze the influence of metro stations on housing prices in different zones.

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