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Are the Effects of Opening New Mass Rapid Transit Segments in Taiwan on Nearby Housing Prices Positive?

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Abstract

This study evaluates the effects of opening new segments of mass rapid transit (MRT) lines on housing prices near the MRT stations in Tucheng District and Xinzhuang District, New Taipei City, Taiwan. The effect of proximity to each MRT station is estimated separately with difference-in-differences regressions integrated with spatial econometrics with heteroscedasticity-robust standard errors. The opening of the new segment of the Blue Line, also known as Bannan Line of the Taipei Metro, does not significantly influence housing prices within 600-metre road network distance of the MRT stations, compared to prices outside the distance range. In contrast, and also unlike the findings of prior studies, although the segment and the stations are underground structures, the opening of the new segment of the Orange Line, also known as the Zhonghe-Xinlu Line of the Taipei Metro, significantly decreases housing prices within 600-metre road network distance of the MRT stations, compared to prices outside the distance range, perhaps because the opening of the stations is delayed about one and a half years to be used as a temporary storage area for MRT trains. The findings have implications for homebuyers, investors, mortgage lending institutions and tax assessment authorities.

Keywords: Hedonic pricing model, housing price, mass rapid transit, public transport, spatial regression

JEL Classification: R31, R40, C21, G21, H20

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Introduction

Mass rapid transit (MRT), also known as metro in Europe or subway in the USA, in contrast to light rail transit, is a type of high-capacity and high-speed passenger urban rail transit which comprises electric railways operating on an exclusive right-of-way without level crossings (Metro Rail News, 2019; RailSystem, n.d.; Texas A&M Transportation Institute, n.d.). Compared to commuter railways, MRT provides high-frequency services to allow its passengers to travel fast and on time between urban areas, thus reducing travel times. Due to its capacity, MRT is considered an efficient and eco-friendly way to provide public transport services on designated lines between stations in urban areas. To address urban transport challenges, governments around the world have been pumping public funding to build new or extend existing MRT systems in their major cities (Suzuki *et al*., 2013; Diao *et al*., 2017). This trend is particularly evident in Asian cities. For example, Dhaka in Bangladesh, Jakarta in Indonesia, Manila in the Philippines, Keelung and New Taipei City in Taiwan, and Ho Chi Minh City in Vietnam are constructing or proposing new MRT lines or MRT sections (DeAeth, 2018; Nhu, 2018; de Vera, 2019; Promchertchoo, 2019; Cuenca, 2020; Everington, 2020).

The accessibility benefits of MRT service are local by nature because people living near MRT stations are more likely to commute by MRT. Urban economics suggests that accessibility of MRT service is relevant to the willingness to pay for locations. Hence, MRT service provision is expected to affect the prices of housing properties within the accessibility range of MRT stations. Whether the MRT service provision effect on price exists is of interest to homebuyers, property investors, financial institutions and local governments. The price information is obviously interesting to homebuyers and property investors wanting to buy or sell at good prices with good timing. Affecting mortgage valuation, the information is important for financial institutions in their mortgage lending decisions. As an influential input for equitable property tax assessments, the price information is interesting to local governments, for whom property taxes are often a vital revenue source for essential services.

There have been empirical investigations about the MRT service provision effect on housing prices in major cities around the world. The international studies mostly apply traditional hedonic price models to capture geographical variations of housing prices reflecting proximity convenience to MRT stations after MRT starts to operate. In contrast, only a limited number of previous studies have examined the temporal changes of housing prices reflecting the provision of access to MRT service. The purpose of the present study is to add to the existing research by evaluating the effects of opening new segments of the MRT lines on the prices of residential properties near the MRT stations in Tucheng District and Xinzhuang District, New Taipei City, Taiwan. An investigation of the opening effects is meaningful because the value of improved accessibility may not be anticipated and reflected correctly in housing prices before the opening day (Zhou *et al*., 2021). In addition, such an investigation can avoid distortion from temporary negative effects associated with the construction of MRT infrastructure (Zhou *et al*., 2021). Moreover, the empirical evidence of the opening effect in academic studies so far is mixed. Besides, market practitioners promote conflicting suggestions as to whether new MRT openings raise housing prices near MRT stations (Chen, 2020; Houseprice.tw, 2020; Chen, 2021). The present study is distinct from and contributes to the literature in the following respects.

Firstly, the present study relaxes the constraint that the effect of proximity on housing prices is the same across MRT stations. Implying the same quality of service, the implicit constraint in prior published studies contradicts the perception that MRT service quality, including destination accessibility, network connectivity, built environment and transit fares, is different across stations (Prasertsubpakij and Nitivattananon, 2012; Li *et al*., 2019). Failure to take the fact in to account could potentially distort the price effect of MRT accessibility provision. To capture the price effect more accurately, this study estimates the effect of each MRT station separately. Secondly, the present study is also the first to employ the difference-in-differences (DID) approach integrated with spatial econometrics with heteroscedasticity-robust standard errors to study the effect of proximity to MRT stations on housing prices. Most prior studies ignore the non-randomness of MRT station location selection and employ a traditional hedonic approach. Some studies adopt the DID approach but neglect the spatial dependence inherent in property price data. A few studies integrate the DID approach with spatial econometrics but fail to tackle heteroscedasticity of regression disturbances. As noted by Kelejian and Prucha (2010), ignoring heteroscedasticity could lead to inconsistent coefficient estimators or inappropriate standard errors, resulting in misleading inferences.

Thirdly, this study adds to the few studies adopting road network distances to measure the proximity of residential properties to MRT stations. Most prior studies use Euclidean distances, which disregard man-made and natural features on the ground and thus potentially distort the estimation of the effect of MRT accessibility provision in densely built-up urban areas. In contrast, proximity measures based on road network distances acknowledging topographic features in urban areas can measure geographic separation in cities more realistically (Diao *et al*., 2017). Fourthly, this study examines the influences of MRT segments in New Taipei City, Taiwan. This geographic setting makes this study distinct from prior studies on the temporal price effects of MRT accessibility provision. Geographically located in northern Taiwan, New Taipei City, surrounding Taipei City, with its over four million inhabitants is the most populous city in Taiwan but has less spatial MRT network coverage than Seoul, Singapore and Taipei City. Residential properties in New Taipei City are more affordable than in Seoul and Taipei City but less affordable than in Singapore (Ministry of the Interior, n.d.; Kim and Kim, 2019; Cox and Pavletich, 2019).

The rest of this paper is organized as follows: Section 1 reviews relevant literature. Section 2 describes the data collection and empirical models. Section 3 presents and discusses the empirical results. Section 4 concludes the paper.

1. Literature Review

The bid-rent theory envisions negative relationships between real-estate prices and transport costs in location choices (Alonso, 1964; Muth, 1969; Mills, 1972). In residential location choices, the theory predicts a negative housing price gradient with respect to commuting costs. By saving travel time, passenger railways reduce commuting costs and their accessibility is thus expected to enhance housing prices. Following the increased importance of MRT as an urban rapid rail service, research attention has moved to MRT stations recently. However, the actual effects of MRT accessibility on housing prices are still not well understood.

The international studies mostly reveal positive impacts of proximity to MRT stations on nearby housing prices. Applying traditional hedonic price models, most of the studies focus only on the impacts after MRT starts to operate. However, some of the studies have documented anticipation effects related to MRT openings. For Seoul, Korea, Bae *et al*. (2003) showed evidence supporting that the price effect of MRT opening was anticipated and reflected significantly and positively from the year of announcement up to the year of opening, and then evaporated. For Chicago, USA, McMillen and McDonald (2004) also found that housing prices near MRT stations rose prior to the MRT opening. However, they found the housing prices close to the stations to be still higher after the MRT line opened. For Sydney, Australia, Chen *et al*. (2019) also found a positive impact of proximity to MRT stations at the construction stage but documented a negative impact at the announcement stage.

In addition, some studies have examined how prices of residential properties near MRT stations change over time across different stages of MRT projects. Zhou *et al*. (2021) utilized repeat sales data to examine the opening effects of MRT in Shanghai, China. Surprisingly, they reported that every 1 kilometre in road network distance closer to the nearest MRT station led to declines of 1.84% to 16.36% in housing prices over time attributable to the opening of MRT. Noticing that some of the MRT stations are on the ground, they attributed the housing price depreciations to the noise problem after the MRT starts to operate. To avoid the possible sample selection bias associated with using repeat sales data, the following studies have turned to the difference-in-differences (DID) method. For Santiago, Chile, applying a standard linear DID model, Agostini and Palmucci (2008) reported that prices of flats within 1-kilometre range of the nearest MRT station, compared to other flats, increased significantly by about 5.0% after the MRT line construction announcement and about 4.3% following the release of information on its basic engineering project. For Warsaw, Poland, Trojanek and Gluszak (2018) integrated the DID method with the spatial autoregressive model (SAR), the spatial error model (SEM) and the spatial autoregressive model with autoregressive disturbances (SARAR) to examine the price effects of proximity to the MRT stations. They found no significant price change during the period before construction works begin. However, they found that flats within 1 kilometre radius of the closest MRT stations are sold for about 1.5% to 2% more in the construction phase and for about 4% more than other flats after the MRT opening.

For Singapore, Diao *et al*. (2017) documented that the prices of residential properties located within 600 metres of road network distance from the nearest MRT station, compared to other properties, increase by 10.6% after the opening of the MRT stations. However, integrating the SARAR with the DID method, the authors claimed that the price effects of proximity to the MRT stations were overestimated by 2% by the traditional DID model. For Taipei City, Taiwan, Lee *et al*. (2020) integrated the DID method with the SAR and the SEM to examine the price effects of proximity to the MRT stations. In contrast to the above studies, they found that the prices of residential properties within 500-metre range of the nearest MRT station, compared to properties outside the range, decrease by 7.9% after MRT construction begins. However, they found no significant price change after MRT starts to operate. They attributed the findings to the price overreaction to the announcement of MRT station construction, traffic congestion and environmental externalities caused by construction works, and the price increase after the completion of MRT construction in anticipation of the official beginning of MRT operation.

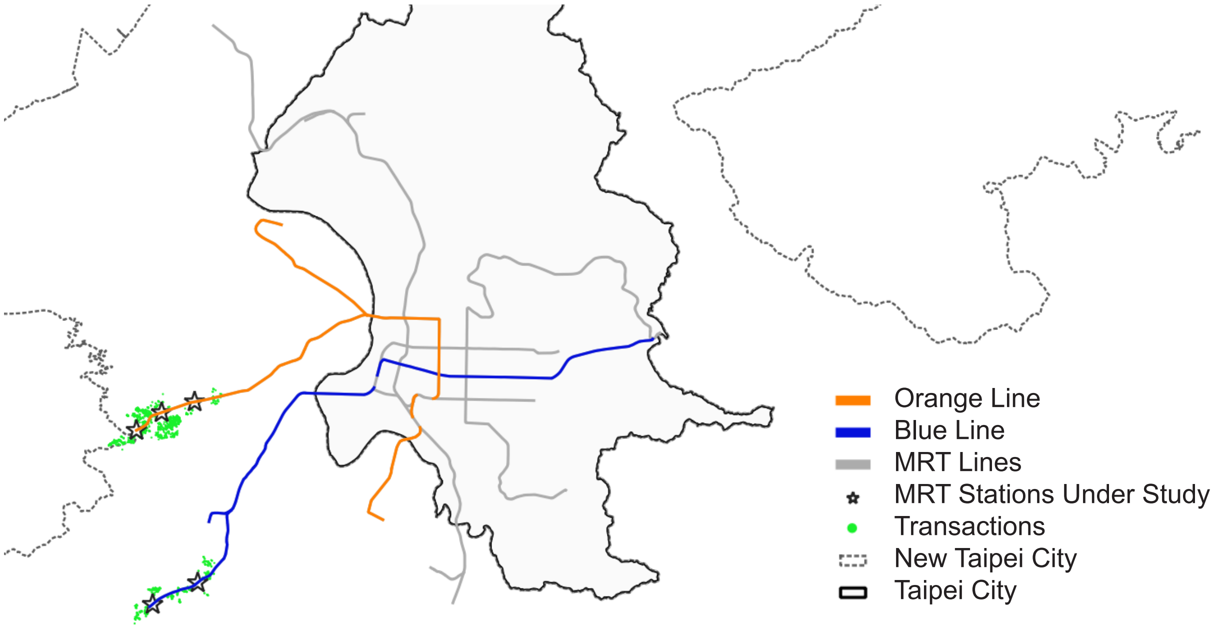
The literature review reveals that the empirical evidence so far is mixed. The review also finds the following. Firstly, almost all the studies constrain the price effect of proximity to the nearest MRT station on nearby residential properties to be the same across MRT stations. Although not exactly making the same constraint, Zhou *et al*. (2021) still constrain the effect to be the same across stations in the same part of Shanghai, China. Secondly, relatively few studies utilize the DID approach to mitigate endogeneity. None of the studies adopting spatial DID approach have tackled heteroscedasticity. Thirdly, most of the studies measure the proximity of housing properties to MRT stations with Euclidean distances or Euclidean distance-based ring buffers. Finally, regarding Asian cities, no studies adopting a spatial DID approach focus on New Taipei City, whose MRT network is relatively less developed.

2. Data Collection and Empirical Models

2.1 Data collection

This study obtains New Taipei City's housing price index and real estate transaction database released by the Department of Land Administration of the Ministry of the Interior, Taiwan. The transaction data are reported by land administration agents paid by sellers and buyers to assist in ownership transfer registration. Starting from 1 August 2012, land administration agents have been obligated legally to report transaction information to the Department of Land Administration. The database includes information on the transaction price, the transaction date and characteristics of the transacted property, such as address, transacted building area, building age, floor number, total number of floors in the building and land use district.

Figure 1: Housing property transactions and MRT stations under study



Source: Authors´own elaboration

The data are collected from 1 August 2012 to 31 December 2018 because of data availability. This study demarcates the study area by a 1.2 kilometre road network distance from the studied MRT stations. The demarcation distance is larger than half of the distance between any two nearby stations under study. After excluding non-housing property transactions, transactions whose prices excluding parking and building areas excluding parking spaces cannot be calculated, transactions with missing data and special transactions, this study retains a total sample of 4,136 housing property transactions for analysis. Figure 1 plots the locations of the housing property transactions and the MRT stations under study with the boundaries between New Taipei City and Taipei City.

The database lacks, however, information on neighbourhood characteristics and accessibility features. Using SuperGIS, a geographic information system software, this study geocodes each transacted property to identify the neighbourhood where each transacted property is located.

Then this study collects population densities and percentages of population with university degree of the neighbourhoods from district affair offices or other public data sources. Obtaining road network layers, this study also uses SuperGIS to measure road network distances to the nearest elementary or junior high school, the district affairs office and MRT stations, instead of Euclidean distances. Road network distances are the walking distances of the shortest road routes while Euclidean distances are straight-line distances ignoring topographic features.

Urban areas are not featureless land and are usually intersected by road networks, scattered with buildings and sometimes traversed by rivers. Obviously, proximity measures based on Euclidean distances are not realistic approximations of geographic separation between housing properties and MRT stations in densely built-up cities. Consequently, Euclidean distance-based measures could distort the estimation of the housing price effects of MRT accessibility provision. In contrast, proximity measures based on road network distances acknowledging the topographic features in urban areas can measure geographic separation in cities more realistically (Diao *et al*., 2017). In this study, the sample mean difference between road network distances and Euclidean distances is around 774 metres, the maximum difference is about 1,198 metres, and the minimum difference is close to 84 metres. The standard deviation of the difference is approximately 239 metres. These statistics illustrate the importance of using road network distances to measure proximity to MRT stations.

This study focuses on the openings of MRT segments in Tucheng District and Xinzhuang District in New Taipei City because their exact dates are available and are after 1 August 2012. Tucheng and Xinzhuang Districts' population densities are 8,015 and 21,165 people per square kilometre respectively. Their percentages of population with a university degree are about 22% and 25% respectively. The segments and the related stations are underground structures. In Tucheng District, the segment from Yongning Station (MRT station number BL02) to Dingpu Station (MRT station number BL01) on the Blue Line (hereafter, the blue segment) commenced operation on 6 July 2015. However, Yongning Station already opened on 31 May 2006, when the segment from station number BL08 to BL02 commenced operation. In Xinzhuang District, the segment from Fu Jen University Station (MRT station number O19) to Danfeng Station (MRT station number O20), then to Huilong Station (MRT station number O21) on the Orange Line (hereafter, the orange segment) commenced operation on 29 June 2013. However, Fu Jen University Station already opened on 15 January 2012, when the segment from station number O13 to O19 commenced operation.

2.2 Difference-in-differences models

As noted by Gibbons and Machin (2005), employing the traditional hedonic approach to study of the effect of proximity to MRT stations on property prices fails to account for a potential endogeneity problem. The problem arises from the fact that MRT stations are not located randomly, but are results of comprehensive urban analysis (Trojanek and Gluszak, 2018). The DID approach is one way to mitigate endogeneity (Meyer, 1995). Applying this approach, this study observes the before-and-after variations in housing prices between influence zones that directly enjoy the effects of operations of the new segments and control neighbourhoods that do not. To define the zones, this study creates five binary variables, $BL02$, $BL01$, $O19$, $O20$ and $O21$ in reference to Yongning Station, Dingpu Station, Fu Jen University Station, Danfeng Station and Huilong Station. The variables have a value of one for an influence zone and a value of zero for a control zone. The four variables are to capture the geographical impact zones of the MRT stations where the new segments operate.

Dewees (1976) defines the influence zones within approximately 540 metres in Euclidean distance from stations. Lee *et al.* (2020) set 500 metres as the cut-off distance to define the influence zone. Diao *et al*. (2017) identify the influence zones within a 600 metre road network distance of MRT stations. Considering that the distances between two nearby MRT stations under study are from 1,364 metres to 1,983 metres, in searching empirical influence zones, this study experiments with 500, 550, and 600 metres in road network distance from MRT stations and obtain qualitatively similar results. Supported by R-squared values, this study decides to define the influence zones with 600 metres in road network distance to demarcate the influence boundaries.

This study also creates two binary variables, *AfterB* and *AfterO*, to separate the pre-existing differences and the differences after the openings of the new MRT segments in the housing prices between influence zones and control zones. The variable *AfterB* defines the opening of the blue segment and takes a value of one on and after 6 July 2015 and zero otherwise. The variable *AfterO* defines the opening of the orange segment and takes a value of one on and after 29 June 2013 and zero otherwise.

The standard linear DID model for the log housing prices is established as follows:

$$\begin{aligned}\ln P = {} & \alpha + \beta_1 \times BL02 + \beta_2 \times BL01 + \beta_3 \times O19 + \beta_4 \times O20 + \beta_5 \times O21 + \beta_6 \times AfterB + \beta_7 \times AfterO \\ & + \beta_8 \times \left(AfterB \times BL02 \right) + \beta_9 \times \left(AfterB \times BL01 \right) + \beta_{10} \times \left(AfterO \times O19 \right) \\ & + \beta_{11} \times \left(AfterO \times O20 \right) + \beta_{12} \times \left(AfterO \times O21 \right) + C'\gamma + \varepsilon \end{aligned} \tag{1}$$

where ln$P$ is the transaction price of a housing property excluding parking space in natural logarithmic form; the DID variables $AfterB \times BL02$, $AfterB \times BL01$, $AfterO \times O19$, $AfterO \times O20$ and $AfterO \times O21$ are to capture the opening effects of the MRT segments specific to residential properties close to MRT stations; ***C*** is a vector of control variables including housing characteristics, neighbourhood characteristics and city-wide market conditions.

Table 1: Summary statistics

	Full sample		**Treatment sample**		**Control sample**	
Observations	4,136		1,045		3,091	
Continuous variable	**Mean**	**St. dev.**	**Mean**	**St. dev.**	**Mean**	**St. dev.**
Transaction price	8,889	4,516	10,240	4,328	8,433	4,488
Transacted area	100.70	41.53	109.10	38.44	97.88	42.15
Building age	11.93	11.32	10.20	11.20	12.52	11.31
Floor number	7.16	4.44	7.63	4.55	7.00	4.39
Building height	12.74	5.37	13.20	5.33	12.58	5.38
Population density	24,559	24,727	19,526	21,344	26,260	25,550
Pop. with uni. deg.	0.24	0.04	0.22	0.04	0.25	0.04
New Taipei City HPI	97.50	6.01	97.95	5.26	97.34	6.24
Road network distance to						
Nearest MRT	775.10	238.80	458.30	125.00	882.20	160.20
Nearest school	558.40	283.90	561.40	189.60	597.50	308.80
District affairs office	3,279.00	998.20	3,395.00	705.50	3,239.00	1,077.00
Categorical variable	Obs.	%	Obs.	%	Obs.	%
First floor	119	2.88	17	1.63	102	3.30
Commercial district	187	4.52	33	3.16	154	4.98
Industrial district	528	12.77	131	12.54	397	12.84
Residential district	3375	81.60	875	83.73	2500	80.88
Q1	852	20.60	245	23.44	607	19.64
Q2	940	22.73	239	22.87	701	22.68
Q3	1100	26.60	226	21.63	874	28.28

Notes: The table contains the transaction price of a housing property excluding parking space, housing characteristics, neighbourhood characteristic variables and city-wide market condition variables. The transaction price is in thousand Taiwan dollars. The transacted building area excluding parking space is in square metres. The population density is in residents per square kilometre. The variable of population with university degree is in percentage. The road network distances are in metres.

Source: Own analysis

The housing characteristic variables are transacted building area excluding parking space, building age, building age squared, floor level, building height, first floor dummy and land use district dummies, including residential district, commercial district and industrial district dummies. The neighbourhood characteristic variables are population densities and percentages of population with a university degree, the road network distance to the nearest elementary or junior high school and the road network distance to the district affairs office. The city-wide market condition variables are quarterly dummy variables and New Taipei City housing price index. Detailed variable definitions are provided in the Appendix.

Table 1 presents the summary statistics of the variables. For the full sample, the average housing price is NT$ 8,889,000 (about US$ 319,683). The average transacted areas are 100.70 square metres (1083.926 square feet). Reflecting the characteristics of high-density living in New Taipei City, the properties on average have about 13 stories. The neighbourhoods where the properties are located have on average 24,559 residents per square kilometre and 24% of their residents have a university degree, reflecting that New Taipei City is a highly developed and populous city in Taiwan. Because of zoning ordinances and their enforcement, not all properties stand in residential districts. Instead, 81.60% of the properties are in residential districts, 12.77% in industrial districts, 4.52% in commercial districts, and the rest in other zoning districts.

Although widely used in applied research on property prices, standard linear models, including the standard DID model, are likely to suffer from significant limitations, mostly relating to heteroscedasticity and spatial dependence (Torzewski, 2020). To tackle this first problem if detected, this study employs either Eicker-Huber-White (EHW-HET) robust standard errors (Eicker, 1967; Huber, 1967; White, 1980) or Kelejian-Prucha (KP-HET) robust standard errors (Kelejian and Prucha, 2010), whichever is appropriate, to account for heteroscedastic disturbances. The second problem relates to Tobler's (1970) first law of geography, which says that things in proximity are more related than things farther away. If this is the case, spatial inter-dependence may exist in housing prices, reflecting spatial spillovers, or in regression errors, thus violating the uncorrelated error assumption of standard linear models (LeSage and Pace, 2009). To deal with the issues caused by spatial dependence, this study re-designs Equation (1) by applying (1) a spatial autoregressive model, (2) a spatial error model, and (3) a spatial autoregressive model with autoregressive disturbances.

The spatial autoregressive model incorporates a spatially lagged dependent variable into Equation (1). The resulting spatial autoregressive DID model (SARDID) is represented below:

$$\begin{aligned}\ln P = {} & \alpha + \rho \mathbf{W} \ln P + \beta_1 \times BL02 + \beta_2 \times BL01 + \beta_3 \times O19 + \beta_4 \times O20 + \beta_5 \times O21 + \beta_6 \times AfterB \\ & + \beta_7 \times AfterO + \beta_8 \times (AfterB \times BL02) + \beta_9 \times (AfterB \times BL01) + \beta_{10} \times (AfterO \times O19) \\ & + \beta_{11} \times (AfterO \times O20) + \beta_{12} \times (AfterO \times O21) + C'\gamma + \varepsilon \end{aligned} \tag{2}$$

where $\mathbf{W}$ is a spatial weight matrix capturing the spatial relations among the properties.

The spatial error model allows spatial autocorrelation among the regression errors of Equation (3). The resulting spatial error DID model (SERDID) is represented below:

$$\begin{aligned}\ln P &= \alpha + \beta_1 \times BL02 + \beta_2 \times BL01 + \beta_3 \times O19 + \beta_4 \times O20 + \beta_5 \times O21 + \beta_6 \times AfterB + \beta_7 \times AfterO \\ &+ \beta_8 \times \left(AfterB \times BL02 \right) + \beta_9 \times \left(AfterB \times BL01 \right) + \beta_{10} \times \left(AfterO \times O19 \right) \\ &+ \beta_{11} \times \left(AfterO \times O20 \right) + \beta_{12} \times \left(AfterO \times O21 \right) + C'\gamma + \varepsilon; \quad \varepsilon = \lambda \mathbf{W} \varepsilon + \nu \end{aligned} \tag{3}$$

where **W**, as before, is a spatial weight matrix defining the spatial linkages among the properties.

The spatial autoregressive model with autoregressive disturbances introduces both a spatially lagged dependent variable and spatial autocorrelation among regression errors. The SARARDID model based on Equation (1) is shown as follows:

$$\begin{aligned}\ln P &= \alpha + \rho \mathbf{W} \ln P + \beta_1 \times BL02 + \beta_2 \times BL01 + \beta_3 \times O19 + \beta_4 \times O20 + \beta_5 \times O21 + \beta_6 \times AfterB \\ &+ \beta_7 \times AfterO + \beta_8 \times \left(AfterB \times BL02 \right) + \beta_9 \times \left(AfterB \times BL01 \right) + \beta_{10} \times \left(AfterO \times O19 \right) \\ &+ \beta_{11} \times \left(AfterO \times O20 \right) + \beta_{12} \times \left(AfterO \times O21 \right) + C'\gamma + \varepsilon; \quad \varepsilon = \lambda \mathbf{W} \varepsilon + \nu \end{aligned} \tag{4}$$

where **W**, as before, is a spatial weight matrix. In the above models, the matrix is a standardized k-nearest neighbour weight matrix based on the longitudes and latitudes of the residential properties (LeSage and Pace, 2014; Torzewski, 2020).

3. Empirical Results and Discussion

3.1 Standard linear DID results

The estimated results from the standard linear DID model represented by Equation (1) are exhibited in Table 2. The table presents the estimated coefficients for MRT-related variables. Model SLM1 is the simplest baseline model containing only the 12 MRT-related variables (2 opening day dummies, 5 influence zone dummies and 5 DID variables) and a constant. Model SLM2 controls for housing characteristics. Model SLM3 also controls for neighbourhood characteristics. Model SLM4 further controls for city-wide market conditions.

Table 2: Standard linear difference-in-differences models

Variable	SLM1	SLM2	SLM3	SLM4
***BL*02**	0.250*** (3.789)	0.170*** (5.109)	0.064** (2.168)	0.064** (2.217)
***BL*01**	0.240*** (4.327)	0.200*** (7.129)	0.303*** (12.729)	0.226*** (11.370)
***O*19**	0.179 (0.800)	0.084 (0.749)	−0.023 (−0.241)	0.004 (0.042)
***O*20**	0.139** (0.050)	0.153*** (4.183)	0.174*** (5.566)	0.164*** (5.372)
***O*21**	0.385*** (7.760)	0.154*** (6.158)	0.136*** (6.394)	0.145*** (6.965)
AfterB	0.152*** (8.949)	0.065*** (7.569)	0.154*** (20.194)	0.133*** (17.409)
AfterO	0.182*** (8.979)	0.147*** (14.035)	0.105*** (11.896)	−0.067*** (−3.698)
***AfterB* × *BL*02**	−0.365*** (−2.967)	−0.088 (−1.425)	−0.088 (−1.697)	−0.078 (−1.548)
***AfterB* × *BL*01**	0.110 (1.542)	−0.029 (−0.797)	−0.032 (−1.067)	−0.022 (−0.738)
***AfterO* × *O*19**	-0.043 (−0.161)	-0.003 (−0.023)	0.056 (0.500)	0.057 (0.525)
***AfterO* × *O*20**	0.026 (0.354)	−0.096** (−2.501)	−0.054 (−1.657)	−0.067** (−2.095)
***AfterO* × *O*21**	−0.383*** (−6.093)	−0.118*** (−3.723)	−0.087*** (−3.283)	−0.080*** (−3.072)
Constant	15.635*** (922.181)	14.999*** (384.459)	17.745*** (345.116)	13.634*** (127.997)
Housing characteristics	No	Yes	Yes	Yes
Neighbourhood characteristics	No	No	Yes	Yes
City-wide market conditions	No	No	No	Yes
Adjusted *R*-squared	0.116	0.779	0.845	0.852
Diagnostic for spatial dependence				
LM (lag)	1812.422***	676.648***	322.798***	320.849***
Robust LM (lag)	120.371***	4.570**	46.133***	68.900***
LM (error)	1695.088***	1493.949***	488.234***	401.721***
Robust LM (error)	3.037	822.050***	211.570***	149.771***
LM (SARMA)	1815.459***	1498.518***	534.368***	470.621***
Diagnostic for heteroscedasticity				
Breusch-Pagan	131.832***	7476.492***	26887.899***	29189.014***
Koenker-Bassett	57.107***	591.971***	940.281***	912.287***

Notes:

1. The table reports the results for the standard linear difference-in-differences regressions with the log -transaction price of a housing property excluding parking space as the dependent variable.

2. *BL*02, *BL*01, *O*19, *O*20 and *O*21 are the binary variables indicating whether housing properties are in areas near MRT station BL02, BL01, O19, O20 and O21 respectively.

3. The variable *AfterB* defines the opening of MRT segment from MRT station BL02 to BL01 in Tucheng District on 6 July 2015. The variable *AfterO* defines the opening of MRT segment from MRT station O19 to O21 in Xinzhuang District on 29 June 2013.

4. The housing characteristic variables are transacted building area excluding parking space, building age, building age squared, floor number, total number of floors, first floor dummy and land use district dummies. The neighbourhood characteristic variables are population densities and percentages of population with a university degree, the road network distance to the nearest elementary or junior high school and the road network distance to the district affairs office. The variables of city-wide market conditions are quarterly dummy variables and New Taipei City housing price index.

5. Students' *t*-values are in the parentheses. ** and *** indicate statistical significance at the 5% and 1% levels respectively.

Source: Own analysis

The baseline model has a very low adjusted *R*-squared value of only 0.116. With the exception of the variable *O*19, the other four influence zone dummies all have positive and significant coefficients. When the DID effects are disregarded, the positive coefficients indicate price premiums of 25%, 24%, 13.9% and 38.5% on average for residential properties located within 600 metres of road network distance from MRT stations BL02, BL01, O20 and O21, respectively, compared to residential properties located outside the influence zones.

The two opening day dummies (*AfterB* and *AfterO*) are both positive and significant at the 1% level. When the DID effects are disregarded, the positive coefficients indicate general positive trends in housing prices, 15.2% and 18.2% price increases, in the studied areas, mainly Tucheng District and Xinzhuang District in New Taipei City, after the openings of the blue segment and the orange segment.

As for the DID variables, their coefficients indicate the DID effects, that is how the price trends mentioned above differ between the influence zones and the control zones. As shown in the table, *AfterB* × *BL*02 and *AFTERO* × *O*21 have statistically significant coefficients but the other DID variables do not. The significant coefficients are negative and thus indicate downward trends in housing prices, 36.5% and 38.3%, in the influence zones *BL*02 and *O*21 compared to the control zones, after the openings of the MRT segments.

Controlling for housing characteristics, as expected, Model SLM2 has a much higher adjusted *R*-squared value of 0.779. Model SLM3 also controls for zone characteristics. The adjusted *R*-squared value further increases to 0.845. In the two models with more controls, the influence zone dummies, except the variable *O*19, still all have positive and significant coefficients. Again, same as in the baseline model, the opening day dummies still have positive and significant coefficients. *AfterO* × *O*21 still has a significant and negative coefficient. *AfterB* × *BL*02, however, has a statistically significant coefficient. However, *AfterO* × *O*20 has a significant and negative coefficient in Model SLM2 but does not in Model SLM3, same as in Model SML1.

Model SLM4 further controls for the city-wide market condition variables. The adjusted *R*-squared value further increases to 0.852 from 0.845. The coefficient of *AfterB* still remains significant and positive. Interestingly, the coefficient of *AfterO* becomes significant but negative. After checking that this is not caused by collinearity, the negative coefficient reveals that, after the city-wide condition is removed, there is a general downward trend in housing prices in the studied areas after the opening of the orange segment. Now both *AfterO* × *O*20 and *AfterO* × *O*21 have significant and negative coefficients, but in smaller magnitudes compared to those in Model SLM3. The significant coefficients indicate downward trends, after the city-wide condition is removed, in housing prices, 6.7% and 8.0%, in the influence zones, *O*20 and *O*21, compared to the control zones after the opening of the segment of the Orange Line.

The adjusted *R*-squared values shows that Model SLM4 provides the best and reasonable fit to the data. Nevertheless, the Lagrange Multiplier test against spatial lag and the robust version of the test both have statistic values statistically significant at the 1% level. The Lagrange Multiplier test against spatial error and its robust version also both obtain test statistic values significant at the 1% level. Furthermore, the joint test statistic of the Lagrange Multiplier test, listed as LM (SARMA), obtains a value of 470.621, statistically significant at the 1% level. Moreover, the Breusch-Pagan test and the Koenker-Bassett test against heteroscedasticity of regression errors also take values significant at the 1% level. The diagnostic results clearly show that Model SLM4 suffers from spatial dependence and heteroscedasticity.

3.2 Alternative models: SARDID, SEMDID and SARARDID

Table 3 shows the results of the models used to tackle the spatial dependence and heteroscedasticity problems found in Model SLM4. As for the *k*-nearest neighbour weight matrix, this study experiments with $k = 1$, 2 and 3 and observes similar results. The reported estimates are from the models based on 2 nearest neighbour weight matrix. Model SARDID shows the estimated result of Equation (2) with EHW-HET robust standard errors. Model SEMDID presents the estimated result of Equation (3) with KP-HET robust standard errors. Model SARARDID presents the estimated result of Equation (4) with KP-HET robust standard errors. Although not exactly the same, the results of the three models are similar qualitatively. In terms of pseudo *R*-squared values, the models are also very similar, especially SARDID and SARARDID.

Table 3: Spatial difference-in-differences models with heteroscedasticity-corrected standard errors

Variable	SARDID	SEMDID	SARARDID
***BL*02**	0.049 (1.723)	0.054 (1.306)	0.043 (1.233)
***BL*01**	0.234*** (10.472)	0.251*** (10.024)	0.227*** (9.638)
***O*19**	−0.009 (−0.110)	−0.025 (−0.246)	−0.029 (−0.333)
***O*20**	0.146*** (7.231)	0.151*** (7.123)	0.142*** (6.787)
***O*21**	0.128*** (9.538)	0.130*** (7.722)	0.122*** (8.257)
AfterB	0.118*** (14.361)	0.104*** (12.939)	0.103*** (12.457)
AfterO	−0.064*** (−3.468)	−0.020 (−0.982)	−0.034 (−1.705)
***AfterB* × *BL*02**	−0.073 (−1.795)	−0.060 (−1.516)	−0.064 (−1.590)
***AfterB* × *BL*01**	−0.019 (−0.771)	−0.005 (−0.203)	−0.010 (−0.400)
***AfterO* × *O*19**	0.048 (0.506)	0.084 (0.796)	0.066 (0.672)
***AfterO* × *O*20**	−0.056*** (−2.590)	−0.055** (−2.409)	−0.052** (−2.342)
***AfterO* × *O*20**	−0.070*** (−3.349)	−0.070*** (−3.615)	−0.067*** (−3.383)
Constant	12.228*** (25.944)	13.924*** (112.933)	12.516*** (31.800)
Housing characteristics	Yes	Yes	Yes
Neighbourhood characteristics	Yes	Yes	Yes
City-wide market conditions	Yes	Yes	Yes
rho	0.092*** (2.982)		0.083*** (3.388)
lambda		0.324*** (11.125)	0.222*** (5.562)
Pseudo *R*-squared	0.862	0.851	0.861
Anselin-Kelejian test	100.573***		

Notes:

1. The table reports the results for the standard linear difference-in-differences regressions with the log -transaction price of a housing property excluding parking space as the dependent variable.

2. *BL*02, *BL*01, *O*19, *O*20 and *O*21 are the binary variables indicating whether housing properties are in areas near MRT stations BL02, BL01, O19, O20 and O21 respectively.

3. The variable *AfterB* defines the opening of MRT segment from MRT station BL02 to BL01 in Tucheng District on 6 July 2015. The variable *AfterO* defines the opening of MRT segment from MRT station O19 to O21 in Xinzhuang District on 29 June 2013.

4. The housing characteristic variables are transacted building area excluding parking space, building age, building age squared, floor number, total number of floors, first floor dummy and land use district dummies. The neighbourhood characteristic variables are population densities and percentages of population with a university degree, the road network distance to the nearest elementary or junior high school and the road network distance to the district affairs office. The variables of city-wide market conditions are quarterly dummy variables and New Taipei City housing price index.

5. *Z*-values are in the parentheses. ** and *** indicate statistical significance at the 5% and 1% levels respectively.

Source: Own analysis

In Model SARDID, ρ is 0.092, which is statistically significant at the 1% level. The positive value supports the inclusion of the spatially lagged housing price. The statistic of the Anselin-Kelejian test is significant at the 1% level and shows that the model still suffers from spatial autocorrelation in regression errors. In Model SEMDID, lambda has a value of 0.324 and is significant at the 1% level, supporting the modelling spatial autocorrelation in errors. In Model SARARDID, ρ is 0.083 and λ is 0.222. Both have positive and statistically significant values. The values support the approach of modelling both the spatially lagged dependent variable and spatial autocorrelation in errors in the same model. The above evidence shows that Model SARARDID is most trustworthy.

As the spatially lagged dependent variable is included, the coefficients in this model only represent direct effects. To be comparable with the interpretation of the standard linear DID model results, following Kim *et al*. (2003) and Small and Steimetz (2012), this study takes into account $\rho = 0.083$ and computes total effects to interpret the results. In this model, three influence zone dummies have positive and significant coefficients. The positive coefficients indicate price premiums of about 24.8%, 15.5% and 13.3%, when the DID effects are disregarded, for residential properties located within 600 metres of road network distance from MRT stations BL01, O20 and O21, respectively, compared to residential properties located outside the influence zones.

The opening day variable defining the opening of the Blue Line, listed as *AfterB,* has a significant and positive coefficient. The value of the coefficient is 0.130. The coefficient indicates, after the city-wide condition is removed, an increasing trend of about 14.2% in housing prices after the opening. The coefficient of *AfterO* is also negative but not significant, indicating no clear trend in housing prices in the studied areas after the opening of the orange segment.

Regarding the DID variables, still only $AfterO \times O20$ and $AfterO \times O21$ have significant and negative coefficients. The significant coefficients indicate downward trends, after the city-wide condition is removed, in housing prices, 5.7% and 7.3%, in the influence zones O20 and O21 compared to the control zone after the opening of the segment of the Orange Line. The coefficients of the other three DIDs remain insignificant, indicating that the price trends do not differ between the three influence zones and the control zones after the opening of the segments of the Blue Line and the Orange Line.

Although not shown in the tables, the housing characteristic variables generally have expected coefficients. As expected, transacted building areas are positively associated with transaction prices of residential properties. Building ages have a negative but statically weak diminishing effect on housing prices. The floor number variable reveals that properties located on higher levels of buildings are more expensive than those on lower levels. The building height variable indicates that properties in high-rise buildings are less expensive than those in low-rise buildings. The first floor dummy coefficient shows that properties on the first floor are sold at a premium. Properties in residential districts appear to be sold at higher prices than in other land use districts. However, the evidence is not very strong statistically.

The neighbourhood characteristic variables all have significant and expected coefficients. Residential properties in neighbourhoods with higher population densities and percentages of population with a university degree are sold more expensively. Properties far from elementary or junior high schools and district affairs offices are less expensive. Quarterly dummy variables show that seasonality of housing prices is evident. As expected, there is strong evidence that residential properties are sold at higher prices when New Taipei City housing price index is higher.

3.3 Discussion

In this study, residential properties in three out the five influence zones of MRT stations are sold at significantly higher prices compared to those located outside the zones, as shown by the influence zone variable coefficients. The finding of significant price premiums is consistent with the findings before MRT station opening documented in most prior studies, including Bae *et al*. (2003) for Seoul, Diao *et al*. (2017) for Singapore and Lee *et al*. (2020) for Taipei City. In contrast, there is no price premium for being in the influence zones of the other two MRT stations, numbered BL02 and O19, in this study. The stations have been in operation for about 6.5 years and 1.5 years before the opening of the studied new segments. The finding of no premium could be consistent with the finding of Bae *et al*. (2003) that the premium on proximity to MRT stations in Seoul evaporates in the third year after opening.

The local general housing price trend significantly increases after the opening of the blue segment, as shown by its opening day variable coefficient. Lee *et al*. (2020) also observed a similar increasing trend in housing prices in their studied area in Taipei City. In contrast, no significant change appears in the price trend after the opening of the orange segment. Notably, Diao *et al*. (2017) even reported a declining price trend for residential properties in their studied area after MRT opening in Singapore. Apparently, the trends simply are local market trends which reflect local variations and could be in any direction.

As expected by the present study, the price impact on nearby residential properties varies across the studied MRT stations associated with the new segment openings in New Taipei City, as shown by the DID variable coefficients. The finding supports the conjecture that MRT service quality varies across stations, and thus their price effects on nearby residential properties differ across stations. This study finds that residential properties near MRT stations O20 and O21 decline in price comparatively after the opening of the orange segment. Moreover, the effects have been anticipated as early as 6 months prior to the opening day. The finding is consistent with the study of Diao *et al*. (2017), who found similar anticipation effects in Singapore. This study also finds that residential properties near MRT stations BL01, BL02 and O19 do not experience significant comparative changes in price after the segment openings. Notably, prior studies document either a significant positive or an insignificant opening day effect. In contrast, this study finds both significant negative and insignificant effects.

For Shanghai, Zhou *et al*. (2021) also found that housing prices near MRT stations declined in response to their opening because of the noise problem caused by the MRT on the ground after the MRT starts to operate. However, the finding of the negative opening effect in this study is not likely attributable to the noise problem because the studied MRT segments and the related stations are underground structures. This was pointed out by Bae *et al.* (2003) in their study on Seoul. To explain their findings in Taipei City, Lee *et al*. (2020) conjectured that the insignificant change in housing price indicates that the effect of opening MRT stations had already been anticipated and reflected fully and correctly before the sample period.

Based on their conjecture, the finding of significant increases in housing price by Diao *et al*. (2017) indicate that the opening effect was not yet fully anticipated and reflected before the opening of the studied MRT stations in Singapore. Along this line of reasoning, the comparative declines in prices of residential properties near MRT stations O20 and O21 in this study could indicate market overreaction in anticipation of the opening of the MRT stations. In fact, some practitioners have attributed declines in housing prices near MRT stations to market overreaction prior to MRT opening (Chen, 2020). In this study, the overreaction might be related to the extra time for speculation, arising from the delay in the opening of the two stations of about one and a half years, to be used as a temporary storage area for MRT trains, because of the protests against demolition of Lo-Sheng Sanatorium to build Xinzhuang Depot in New Taipei City.

Concluding Remarks

Relaxing the implicit constraint of same impact in the literature, the present study examines the price impact of each of the studied MRT stations related to new segment openings separately on nearby residential properties in New Taipei City, Taiwan. Using road network distance instead of Euclidean distance, this study defines more realistic influence zones of MRT stations. To mitigate endogeneity, this study employs the DID approach. To deal with spatial dependence, this study integrates this approach with spatial econometrics. Moreover, the present study utilizes robust standard errors to account for heteroscedastic disturbances.

Several take-away findings emerge from this study. Firstly, the opening effects of the orange segment are significantly negative for residential properties within 600-metre road network distance of MRT stations O20 and O21. The properties decline in price significantly after the opening of the orange segment compared to those outside the distance range. Secondly, the residential properties within 600-metre road network distance of MRT stations O19, BL01 and BL02 do not experience significant comparative price changes.

The findings have implications. For homebuyers, it is not always better to buy residential properties within 600-metre road network distance of MRT stations before their opening. Sometimes, it is better to wait until after the MRT stations start to operate. For investors, it might be better to sell their residential properties situated within 600-metre road network distance MRT stations prior to their opening. When assessing values of residential properties for mortgage lending purposes, financial institutions should take into account the potential market overreaction to the opening effect to make better decisions on mortgage lending. For equitable property tax assessments, local governments should be aware that the opening of MRT stations does not always increase the prices of nearby residential properties.

Appendix: Variable definitions

Variable	Definition
Transaction price	The transaction price of a housing property excluding parking space in thousand Taiwan dollars
Transacted area	The transacted building area excluding parking space in square metres
Building age	Building age in years
Floor number	The floor number of the transacted property
Building height	The number of floors of the building in which the transacted property is situated
Population density	The number of people per square kilometre in the neighbourhood where the transacted property is situated
Pop. with uni. deg.	The percentage of population aged 15 or above with a university degree in the neighbourhood where the transacted property is situated
New Taipei City HPI	New Taipei City housing price index released at the real estate information platform of the Ministry of the Interior, Taiwan
Nearest MRT	Road network distance to the nearest MRT station in metres
Nearest school	Road network distance to the nearest elementary or junior high school station in metres
District affairs office	Road network distance to the district affairs office in metres
First floor	Dummy variable coded 1 if the transacted property is located on the first floor and 0 otherwise
Commercial district	Dummy variable coded 1 if the transacted property is located in a commercial district and 0 otherwise
Industrial district	Dummy variable coded 1 if the transacted property is located in an industrial district and 0 otherwise
Residential district	Dummy variable coded 1 if the transacted property is located in a residential district and 0 otherwise
Q1	Dummy variable coded 1 if the property transaction is in January, February and March and 0 otherwise
Q2	Dummy variable coded 1 if the property transaction is in April, May and June and 0 otherwise
Q3	Dummy variable coded 1 if the property transaction is in July, August and September and 0 otherwise

Source: Own analysis

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