Suburban Housing Creation: Result of Transit Network Expansion in Central City

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Abstract

Housing affordability is often concerning in superstar cities. Like the Taipei metropolis, housing is too expensive in the fully built-up central city, but jobs are there. How can the government incentivize developers to create new housing in areas where households need not be stretch commuters? This research analyzes how public-transport network expansion in the central city of Taipei induced new housing projects in distant suburbs with metro services. Difference-in-differences assesses the impacts of two metro lines' completions on neighborhood housing prices; a 1% better commuter market access increased home values by 0.33%. For every neighborhood, land values of homes are uncovered to gauge average land price and construction permits are used to aggregate new housing launches, resulting in a balanced panel of annual neighborhood data. IV Tobit addresses demand-supply determination and contextualizes developable lands as real options, with commuter market access instrumenting land prices. Consistent with theory, developments are stimulated by returns but deterred by uncertainty. Outside the central city of Taipei, annual housing construction was 2.26% more in housing units and 4.00% more in gross floor area in neighborhoods with metro-station access than those without. A 1% better commuter market access increased the annual construction by 2.47% in units and 3.76% in GFA. Transit network expansion to cover more places in the central city can stimulate housing construction in commutable suburbs where citizens can enjoy relatively more affordable housing and mobility at the same time. We recommend a policy for the sustainable development of real estate, public transportation, and cities.

Keywords: housing affordability, housing supply, superstar cities, real option, public transport, transit oriented development

JEL codes: R00, R21, R31, R38, R40, H42, L92

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1. Introduction

This research concerns how local authorities may work together to tackle housing affordability. Specifically, the study shows that the central-city government can tap into expanding its local public transport network coverage of workplaces. The expansion can generate spillovers of commuters' market access and incentivize new housing developments in surrounding satellite cities or commuter towns, allowing central-city employees to enjoy more affordable housing without being stretch commuters.

The research is motivated by the miseries of housing affordability among the middle and working classes in the world's vibrant cities with an inelastic housing supply. Whether a consumer or production side factor or both, the beauty of these superstar cities appears to be the root cause of the growing tension. These cities are short of new housing construction and fail to keep housing affordable for ordinary families because a fast-growing affluent population demand housing there (Gyourko et al., 2013).

The tension can be exacerbated by globalization, which eases high-income households' cross-border mobility; urbanization, which leads domestic migrants toward core regions; or financial liberalization, which gives preferential credit access to wealthier property investors. Indeed, superstar cities are often the most globally integrated cities or the national or regional capitals, and they are usually the most innovative, high-tech, or financial-center cities with concentrations of world GDP (Manyika et al., 2018). The agglomeration economies are indispensable, but the cities also need key workers and young professionals besides the affluent. After all, "a world in which only a few can afford housing is not sustainable" (Deng et al., 2019). Unaffordable housing hurts people's well-being and causes resentment in the public (Saiz, 2023). The woe could lead to social or political consequences.

Thus, tackling housing affordability is critical to urban sustainability. Especially superstar cities are places contributing to the global housing affordability crisis. Saiz (2023) suggested that making the housing supply more elastic is an affordable housing strategy achievable through relaxed planning restrictions, transportation investment, or decentralized development. Nevertheless, the planning needs to rule out unintended consequences.

For example, when a superstar city marches forward, and central-city housing becomes too expensive to reach for ordinary families, a rational choice is to trade off commuting time against housing prices. The increased "affordability distance" found by Ben-Shahar et al. (2020) is evidence. However, living further away is not necessarily more sustainable. Suburbanization has been phenomenal in major US cities over decades, facilitated by inexpensive vehicles and comprehensive highways. Such car-dependent sprawling is perceived as an unsustainable way of urban development in this era challenged by climate changes, and public-transit-oriented development is reckoned a more sustainable approach (Camagni et al., 2002).

How can public policy incentivize the private sector to create new housing quantities supplied in locales where households need not be stretch commuters, thereby improving overall housing affordability in the metropolitan area and supporting transit-oriented development? This paper sheds light on the big question by studying public transport network expansion in Taipei, an Asian global city. Asia was chosen, for it is the most mountainous and most populated continent on Earth.[1] Furthermore, the developed or emerging Asian economies all gained their success through welcoming international trade and embracing globalization, and thirdly, the rapid urbanization exhibited in Asia is expected to continue.[2] These reasons imply that the superstar city syndrome is more likely to occur in Asian urban areas, and an analytic solution in the Asia context is valuable. Taipei is studied, for it is a classical superstar city with an abysmal price-to-income ratio for housing; the next section elaborates.

The paper shows that public transport network expansion through the completion of new metro lines in the central city of Taipei metropolis eventually induced new housing projects in distant suburbs with the metro services. By incorporating popular destinations in the central city (i.e., Taipei City) into the metro service coverage, the new lines improved commuter market access (CMA) in the suburbs (i.e., New Taipei City) near metro stations and hence increased households' willingness to pay for these convenient suburbs, thereby pushing up local land values and motivating developers to use their land bank there to launch new housing projects.

Specifically, the research studies two major metro lines—Xinyi Line opened in November 2013, and Songshan Line opened in November 2014—servicing Taipei City's prime areas, including several most notable workplaces like Taipei 101 and entertainment hubs like Taipei Arena. It adopts the inconsequential places approach (Chandra and Thompson, 2000; Redding and Turner, 2015) and uses the transport infrastructural development in Taipei City to analyze housing market impacts in New Taipei. For the analysis, we collected housing-transaction and building-construction-permit microdata of New Taipei, station-specific passenger volumes and system information of Taipei Metro, and other supplementary data.

The research design addresses both sides of the housing market. The investigation starts with a demand-side inquiry on households' willingness to pay through hedonic pricing. The difference-in-differences analysis overcomes collinearity and evaluates two continuous treatments of the two metro lines. It shows that a 1% improvement in CMA increased housing prices by 0.33% on average.

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[1] See https://education.nationalgeographic.org/resource/Continent/
[2] https://www.adb.org/features/facts-and-data-about-cities-and-urbanization-asia

Subsequent house price decomposition uncovers the associated land values of transacted properties. Hence, we can gauge each neighborhood's average land value. Besides, we look into building construction permits to aggregate each neighborhood's new housing launches. These result in a balanced panel of annual data at the neighborhood level.

The second part of the analysis focuses on the supply side. It inquires whether the increased willingness to pay for land caused by the improved CMA can increase the land value enough and stimulate new housing construction. This question per se concerns profit-maximizing decisions of developers who take lands as real options. Since lands are freehold and land banking is lawful, developers wait for the optimal development timing. New housing construction can be completely absent in neighborhoods.

Thus, we design an IV Tobit model, akin to Gyourko and Saiz (2004), to contextualize lands as real options. The CMA treatments are incorporated as instruments for land value since they are not in the developers' Lagrangian for profit maximization and only indirectly relate to new housing construction. The results are consistent with the real-option theory that a higher return stimulates development, but greater uncertainty deters it. Through the analysis, we conclude that outside the central city of Taipei metropolis, annual housing construction was 2.25% more in housing units and 3.99% more in gross floor area in neighborhoods with metro-station access than those without. In addition, the annual construction was 2.48% more in units and 3.77% more in GFA in a neighborhood with 1% better CMA than an otherwise identical neighborhood covered by the metro transit services.

Transit network expansion to cover more places in the central city can generate a network-mediated spillover effect (Jing and Liao, 2023) that improves commuter market access (CMA) and increases the supplied housing quantities in commutable suburbs where citizens can enjoy relatively more affordable housing and mobility at the same time. The research finding has practical implications: Investment in public transportation can be a policy instrument to ease overall housing affordability for households and support transit-oriented development. Private developers are motivated to build. Local governments of the superstar city and surrounding satellite cities benefit from political stability or improved public finance. The changes help sustainable real estate and urban development.

Our study fundamentally differs from Lutz et al. (2023), which also concerns housing supply and transit-oriented development. We take transit network expansions as policy shocks in an environment with no change in zoning codes and examine how improved commuter market access caused higher neighborhood land values that motivated developers to launch housing projects in distant, commutable suburbs. On the other hand, the policy shock in Lutz et al. (2023) is an ordinance of a preferential plot ratio of Zurich for areas serviced by more metro lines; their context involves no change in the metro system.

The remaining paper is organized as follows. Section 2 offers the background of Taipei to convey the housing situation and public-transport development of the metropolis. Section 3 discusses data, and Section 4 introduces the methodology in detail. Section 5 presents and analyzes the results. Section 6 makes the conclusion and policy recommendation.

2. Background: Housing Affordability and Metro Transit in Taipei and New Taipei

Taipei City is a classical superstar city depicted by Gyourko et al. (2013). It is an Asian global city in the world's 21st-largest economy, Taiwan.[3] Its settlement began in the 18th century aside from the indigenes, and rapid urbanization occurred upon two million mainland immigrants' arrival after the Chinese civil war. Fuelled by US economic aid initially and sustained by export-oriented growth subsequently, urbanization continued in the following decades, and Taipei City evolved into the island economy's dominant growth center. In 2022, the city contributed 36% of total tax revenues from Taiwan's 22 cities and counties.[4] Its total number of registered businesses and firms grew 12.4% from 2012 to 2022.[5] The demand for housing has constantly risen over the decades.

On the other hand, an inelastic housing supply has become a stark feature of Taipei City. Situated in the east part of Taipei Basin, the city is adjacent to a wide river at the west and tall mountains on the three other sides, as Figure 1 exhibits.[6] The geographic constraints confine buildable areas to about the same size as the San Francisco County, CA of the United States. Furthermore, much of the city is subject to a stringent building height constraint due to the Songshan Airport for commercial and military uses. Most lands and properties are freehold by law, and redevelopments need all landlords' consent. The geographic (physical) and institutional (regulatory) constraints, the two critical factors in housing supply inelasticity (Saiz, 2010), limit housing developments.

[Insert Figure 1 here]

The tension between the rising housing demand and the constrained supply intensified and became an agonizing issue in Taipei. In August 1989, two years after the termination of the five-decade-long martial law, over 50 thousand protesters appealed for affordable housing and slept on Taipei City's most expensive road upon the city's price-to-income ratio exceeded 17.

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[3] The ranking is from the 2023 World Economic Outlook of IMF, which distinguishes economies in China Circle separately.
[4] The percentage is based on data released by Taiwan's finance ministry.
[5] The growth rate is based on data released by Taipei Department of Budget, Accounting, and Statistics.
[6] Taipei city has confined buildable areas, facing Tamsui River at the east, Keelung River and Shichi Moutain (3,674') of Datun Volcano Group at the North, Nangang (1,230') and Shiding (2,755') Mountain Ranges at the East, Shizitoushan (2,814') of Xueshan Mountain Range at the South.

The striking No Shell Snail Movement made the government promise public housing expansion. Housing affordability had notably improved in the 1990s, but the government permanently ceased public housing production in 1999 due to the high costs of land acquisitions.

Table 1 illustrates worrisome housing affordability figures. The mortgage-payment-to-income ratio was consistently high and ranged between 56% and 67% from 2013 to 2019, suggesting that Taipei City's middle-income households could exhaust more than half of their income for mortgage repayments. This potential debt burden far exceeded the recommended ratio of the 28/36 rule that households should not spend more than 28% of gross income on housing expenses.

[Insert Table 1 here]

Table 2 depicts a simulation to shed light on two questions. How affordable is Taipei City housing at various price percentiles to the city's median-income household? Is New Taipei City housing more affordable to this household? As in Panel A, the median-income household of Taipei would have to spend 14 years of disposable income to pursue a $P_{50\%}$ median-priced home. Even for a $P_{25\%}$-priced home, it still required 9 years of disposable income. The ratio for the $P_{10\%}$-priced home appeared more comfortable to this median-income household.[7] Yet, how about lower-income households?

[Insert Table 2 here]

A home in New Taipei would be much more affordable to this median-income Taipei-City-sider, shown by Panel B. The price-to-income ratios were reduced to 10 and 7 for $P_{50\%}$- and $P_{25\%}$-priced homes, respectively. The question is how much sacrifice in time for commuting to Tapei City does one need to make to benefit from relatively more affordable housing in New Taipei? Convenient public transportation is necessary given the heavy traffic in the Taipei metropolis.

Mass rapid transit is the most popular public transportation mode for commuters in the Taipei metropolis, and the services are provided by Taipei Metro. The economic metropolis comprises Taipei City (the 12 districts marked by blue lines in Figure 1) and the part of New Taipei City within the west part of Taipei Basin (the 11 districts marked by amber lines in Figure 1).

Established in 1996, Taipei Metro has gradually expanded its services. Figure 2 exhibits its year 2015 system map with added dashed lines to distinguish between the metro stations in Tapei City and New Taipei. The system comprised five major lines developed in phases. Initially, much effort was made to connect Taipei City—the central city of Taipei metropolis—

[7] The city-state Singapore has a worldwide reputation of affordable housing. The government's commitment is to keep the price-to-income ratio about five for the great majority of households.

with its satellite cities in New Taipei, and many popular destinations in Taipei City were not yet incorporated into the system.

[Insert Figure 2 Here]

The Xinyi and Songshan lines are two milestones of the Taipei Metro. Xinyi Line *opened in November 2013* is a part of the Red Line, and Songshan Line *opened in November 2014* is a part of the Green Line. The two lines service Taipei City's prime areas and incorporate several notable workplaces (e.g., Taipei 101—the world's tallest building, 2004-2010) and entertainment hubs (e.g., Taipei Arena) into the system coverage, allowing commuters from New Taipei or in Taipei to access these popular destinations more conveniently.

3. Data

For empirical analysis, we collected the following data from various agencies. Housing transactions are from the Ministry of Interior's Real Price Registration System, and building construction permits are from the New Taipei City's Public Works Department. The collected data comprise all available records but are limited to New Taipei's 11 districts within the Taipei Basin (see Figure 1) because the study focuses on housing demand and supply there. The sample spans from January 2013 to December 2019 to avoid contamination with the COVID shock and the previous phases of Taipei Metro's system expansion.

The housing transaction dataset has each sold property's price, date, and comprehensive housing characteristics. We exclude the sales between relatives and friends as those transactions do not reflect the market price. The addresses of properties are available; hence, detailed locational attributes are identified, including the distance to the nearest metro station. Several GIS-related utilities were used to pin down the locations of urban amenities. These include GIS-T Transportation Network Geographic Information System for metro stations, bus stations, and highways. Park locations are from New Taipei City's Agricultural Bureau, and the location of Taipei Train Station is from Google Maps. Lastly, complete housing transaction data for 2020 were also obtained for generating the price volatility variable.

The dataset of construction permits details the groundbreaking date, number of homes, gross floor area, and address of each building. It allows us to aggregate quantities of new housing constructions by our delineated neighborhood and year. Non-residential buildings are excluded.

Because very old buildings' data are unavailable or may be inaccurate, we do not attempt to aggregate existing housing stock. Thus, our estimate is not the elasticity of supply but the elasticity of new housing development. While the two elasticity measures are correlated, the development elasticity can be much higher (Mayer and Somerville, 2000; Murphy, 2018).

Commuter market access is a key variable in the analysis, and we calculated this index value for each metro station in New Taipei before Xinyi Line's opening, after that opening, and after Songshan Line's opening. The index calculation of the three timings requires two pieces of information. First, we obtained the travel time between each pair of stations through the existing system's fastest route, including the average time in line haul of commute and wait at departure and transfers. Second, we found every station's monthly total passenger volume and calculated its average annual volume for 2013, 2014, and 2015. These pieces of information originate from Taipei Metro's releases.

Two sources of supplementary data are used to calculate housing affordability measures presented in Table 2 earlier. One is the Ministry of Interior's Real Price Registration System for housing prices. The other is Taipei City Government's Department of Budget, Accounting, and Statistics for the median disposable income.

4. Methodology

This section presents the empirical methodology comprising five parts. The first introduces the commuter market access (CMA) index and micro-foundations. The second lays out the approach to classify subjects into the treatment or control group. The third is the difference-in-differences (DD) that examines housing transaction data and evaluates households' willingness to pay for CMA. The fourth concerns separating properties' land values from housing prices and deriving neighborhood-level land prices. The last part introduces the IV Tobit model for panel data analysis of neighborhood new housing construction.

4.1 Commuter Market Access (CMA) Index

The algorithm is as follows to construct the commuter market access (CMA) index. Let N be either the total number or the whole set of stations of Taipei Metro covering both Taipei and New Taipei cities, and $t_{n\rightarrow n'}$ denotes the travel time (the sum of average time in waiting, line haul, and transfer) from station n to n' through the fastest route. For $\forall \{n, n'\} \subset N$, we calculate the node accessibility $t_{n\rightarrow n'}{}^{-\lambda}$, where the λ of this negative power function governs the decay in accessibility by travel time. Following Jing and Liao (2023), we calibrate and set $\lambda=0.3$ for empirical analysis. Alternative values are also used to test the result's sensitivity and robustness.

The CMA follows a conventional formula in the economic literature:

$$CMA_n = \sum_{n' \in N;\, n' \neq n} t_{n\rightarrow n'}{}^{-\lambda} \times Q_{n'}, \qquad \forall\, n \in N \tag{1}$$

where $Q_{n'}$ is a weight concerning the destination n's economic condition. The formula's micro-foundations are in Ahlfeldt et al. (2015), whose general equilibrium theory proves that the CMA results from commuting market clearing and positively relates to housing prices. Like Ahlfeldt et al. (2015), other applied theories (e.g., Donaldson and Hornbeck, 2016; Tsivanidis, 2018; Jing and Liao, 2022) that incorporate Eaton and Kortum (2002) framework can derive various market access contexts. These spatial equilibrium models show that local economic outcomes are functions of market access, and the functions suit reduced-form analysis (Jing and Liao, 2023).

Here, we approximate $Q_{n'}$ by the average monthly total passenger volume of station *n'* during the year. Locations attracting high volumes of passengers have larger clusters of offices or consumer amenities that citizens need or want to access. Such locations should be weighted more, and good accessibility to these locations will more substantially raise the overall CMA of station *n*.

Let $N_{NTPE} \subset N$ be the whole set of stations in New Taipei. $\forall\, n \in N_{NTPE}$, we use Eq. (1) to obtain three log CMA values: $\ln CMA_n^{pre-E1}$ before Xinyi Line's opening (event 1), $\ln CMA_n^{E1}$ after that opening, and $\ln CMA_n^{E2}$ after Songshan Line's opening (event 2). With them, we can derive two log changes of CMA. We define $\Delta \ln CMA_n^{E1} = \ln CMA_n^{E1} - \ln CMA_n^{pre-E1}$ and $\Delta \ln CMA_n^{E2} = \ln CMA_n^{E2} - \ln CMA_n^{pre-E1}$ for a technical reason explained later.

4.2 Treatment Boundary Estimation

The $\Delta \ln CMA_n$ arising from a transit system expansion is a continuous treatment variable, but this treatment pertains to homes from which a metro station is accessible. Proximity to a metro station is essential to benefit from an improved CMA, but the appropriate threshold distance to define proximity can vary across regions. While Western studies often use 800 meters as the threshold, this distance could be longer in Taipei's context because Taipei siders often ride motor scooters for short travels, such as the "first mile" to neighborhood metro stations.

Thus, this research adopts Jing and Liao's (2023) approach to estimating the threshold distance for the treatment-control classification. Homes within *d* meters of the nearest station are treated, and those further away are not. The estimation procedure is as follows. It adopts the whole sample, which comprises all transacted homes within 2 km of any metro station in New Taipei, for a hedonic regression to predict home prices orthogonal to housing characteristics and transaction time.[8] Then, it applies the locally weighted scatterplot smoothing to estimate a general relationship between the predicted home price and distance to the nearest metro station

[8] The regression function is $\ln P_{it} = \beta_0 + X_{it}\gamma + \theta_t + \varepsilon_{it}$ in which X_{it} and θ_t control the same sets of housing characteristics and year-month fixed effects as the main regression Eq. (4). The predicted house prices are $\ln \hat{P}_{it} = \hat{\beta}_0 + \hat{\varepsilon}_{it}$.

nonparametrically. Subsequently, the entire locus of the predicted price-distance function is traced, and data points are recorded at every 50-meter increment from the origin to the end.

Figure 3 plots these recorded data points. Interestingly, the predicted locus exhibits a similar pattern to Jing and Liao's (2023) study on Singapore's metro transit. The locus shows a downward trend that is initially concave and subsequently convex, and beyond a certain point, the price-distance relationship is flat. There is a threshold distance beyond which households' marginal willingness to pay is trivial for living closer to the metro station. The lack of marginal willingness to pay suggests that the station is too far to commute from the home, so the household has no incentive to trade off the home price marginally against commuting time. To capture this threshold distance better, we specify a two-knot spline regression, which deviates from Jing and Liao's (2023) one-knot setting, because the sharp falling price in the distance starts at a longer distance than their case.

[Insert Figure 3 here]

The two-knot spline regression is specified as follows:

$$\ln P_i = \alpha_0 + \alpha_1 MRT_{k1} + \alpha_2 MRT_{k2} \\ +\beta_0 D\_MRT_i + \beta_1 D\_MRT_i \times MRT_{k1} + \beta_2 D\_MRT_i \times MRT_{k2} + \varepsilon_i \quad (2)$$

This function comprises two dummy variables MRT_{k1} and MRT_{k2} relating to knots *k1* and *k2*, respectively. $MRT_{k1} = 1$ if the *i*-th data point is more than *k1* meters away from the metro station and 0 otherwise, and MRT_{k2} is similarly defined. The continuous variable D_MRT_i is the *i*-th point's distance to the station.

The recorded data and Eq. (2) are repeatedly used to complete a sequence of spline regressions through a two-layer looping procedure. The first loop starts from *k1*=50 until *k1*=1900, with an increment of 50 at each round. The second loop is embedded in the first and starts from *k2*=*k1*+50 until *k2*=1950, with an increment of 50 at each round. Upon completion of the whole sequence of regressions, the one that maximizes the R^2 best fits the nonparametrically estimated locus, and its $\widehat{k2}$ defines the threshold distance.

Figure 3 also plots the best-fit spline function, whose regression achieves the highest R^2 with $\widehat{k1}$=550 and $\widehat{k2}$=1200. The estimated spline function matches the locus well. Thus, we adopt 1200 meters as the threshold distance to define metro-station proximity.

With this result, we define a dummy variable $MRT_{1200} = 1$ for homes within 1.2km of any station; otherwise, $MRT_{1200} = 0$. That said, transacted homes within 1.2 km of the nearest station *n* are treated and affected by the $\Delta\ln CMA_n^{E1}$ and $\Delta\ln CMA_n^{E2}$ of station *n*. Those beyond 1.2 km from any station belong to the control group, and we set $\Delta\ln CMA_n^{E1} = 0$ and $\Delta\ln CMA_n^{E2} = 0$ for them.

4.3 Difference in Differences

With the Xinyi and Songshan line openings as the two treatment events and the estimate of 1.2km as the treatment boundary, we can apply housing transaction data for difference-in-differences (DD) analysis. The baseline DD model incorporates two treatment events and is an extension of the design of Jing and Liao (2023).

If we were to use their specification catering to a single treatment event without modification, the model specification in our research context would be:

$$\begin{aligned}\ln P_{idnt} = \beta_0 + \beta_1 T_{after} + \beta_{DD} \Delta \ln CMA_n \times T_{after} + X_{idnt}\psi + Z_{idnt}\gamma \\ + MRT_{1200} \times MRT_n\, \mu_{1200,n} + \delta_d + \theta_t + \varepsilon_{idnt} \qquad (3)\end{aligned}$$

In Eq. (3), $\ln P_{idnt}$ is the log price of property i transacted at time t that was in district d and nearest to station n, and ε_{idnt} is the error term. The vector X_{idnt} includes the property's comprehensive housing-specific characteristics. The vector Z_{idnt} consists of the home's locational characteristics, including the zoning feature, distances to the nearest park, highway, and bus station, and distance to Taipei Train Station—the gateway to enter Taipei for metro-transit commuters from New Taipei.[9]

Two sets of location fixed effects are in Eq. (3), besides time fixed effects θ_t. These include district fixed effects δ_d and $MRT_{1200} \times MRT_n$ fixed effects, for which $\mu_{1200,n}$ denotes the corresponding fixed effect estimators. The fixed effect vector $MRT_{1200} \times MRT_n$ is a set of interaction terms. The variable $MRT_{1200} = 1$ for houses within 1.2km of any station, and $MRT_{1200} = 0$ for homes further away, based on the treatment boundary estimate. MRT_n is a station-specific dummy variable that equals 1 for homes closest to station n among all N_{NTPE} stations, regardless of whether these homes are within 1200 meters of station n. Thus, $MRT_{1200} \times MRT_n$ delineates $2 \times N_{NTPE}$ locations and $2 \times N_{NTPE}-1$ location fixed effects. We adopt two-way clustering of standard errors at both district and $MRT_{1200} \times MRT_n$ levels whenever it is methodologically feasible.

$\Delta \ln CMA_n$ is a continuous treatment variable concerning the commuter market access improvement caused by the opening of a new metro line. As per normal of DD, $\forall\, n \in N_{NTPE}$, the value of $\Delta \ln CMA_n$ applies to homes with $MRT_{1200} \times MRT_n = 1$ regardless of the transaction time, and $\Delta \ln CMA_n = 0$ if $MRT_{1200} = 0$. The post-treatment indicator $T_{after} = 1$ for homes transacted after the opening event whether treated or not; otherwise, $T_{after} = 0$.

Notably, the $MRT_{1200} \times MRT_n$ fixed effects absorb all sources of time-invariant unobservables, including those correlated with MRT_{1200}, $\ln CMA_n$, or $\Delta \ln CMA_n$. Also, $MRT_{1200} \times T_{after}$ should not be included. The reasons and supporting empirical experiments are detailed in Jing and Liao (2023).

[9] Taipei city is rather polycentric. However, commuters from New Taipei entering Taipei must go through a metro station near the Taipei Train Station. One can notice this necessity by examining the Metro system map of Figure 2. Thus, controlling New Taipei residents' distance to Taipei Train Station is equivalent to controlling their distances to all business centers.

However, Eq. (3) is inapplicable to our study because the gap was only one year between the openings of the Xinyi and Songshan lines, which are two major subways servicing the central city of the Taipei metropolis. Although we could slice the sample period into two and study the two events' treatment effects separately, the short gap between the two times of major CMA enhancement makes such a strategy an inferior approach prone to contamination.

Thus, we must modify Eq. (3) to incorporate the DD over two treatment events in the regression to suit our research context. The modification leads to the specification below:

$$\ln P_{idnt} = \beta_0 + \beta_{\mathrm{E1}} T_{after}^{E1} + \beta_{DD}^{E1} \Delta \ln CMA_n^{E1} \times T_{after}^{E1} + \beta_{\mathrm{E2}} T_{after}^{E2} + \beta_{DD}^{E2} \Delta \ln CMA_n^{E2} \times T_{after}^{E2} + X_{idnt}\psi + Z_{idnt}\gamma + MRT_{1200} \times MRT_n\, \mu_{1200,n} + \delta_d + \theta_t + \varepsilon_{idnt} \tag{4}$$

In a nutshell, $\Delta \ln CMA_n^{E1}$ and $\Delta \ln CMA_n^{E2}$ are station n's commuter market access enhancement that local residents would experience upon Xinyi and Songshan lines' openings, respectively. Without loss of generality, two adjustments are made to reduce collinearity between $\Delta \ln CMA_n^{E1} \times T_{after}^{E1}$ and $\Delta \ln CMA_n^{E2} \times T_{after}^{E2}$. First, $T_{after}^{E1} = 1$ iff the transaction occurred between the two events, and $T_{after}^{E2} = 1$ iff the sale was after the second event. Second, $\Delta \ln CMA_n^{E1} = \ln CMA_n^{post-E1} - \ln CMA_n^{pre-E1}$ and $\Delta \ln CMA_n^{E2} = \ln CMA_n^{post-E2} - \ln CMA_n^{pre-E1}$.

We test the null hypothesis that $\beta_{DD}^{E1} = \beta_{DD}^{E2}$ after performing the regression of Eq. (4) to examine whether the two treatment-effect estimates, which both concern the slope effect of CMA improvement, are statistically the same. Since $\Delta \ln CMA_n^{E2} > \Delta \ln CMA_n^{E1}, \forall n$ by construction (see Section 4.1), a rejection of the null hypothesis would imply concavity or convexity in the response of housing prices in treatment intensity; the caveat of selection cautioned by Callaway (2021) then surfaces. On the other hand, an acceptance of $\beta_{DD}^{E1} = \beta_{DD}^{E2}$ lends support to homogeneous response in treatment intensity, and the regression can identify the average causal response on the treated, as Callaway (2021) suggested.

The parallel trend assumption needs validation, and the event study is the conventional test. The empirical challenge is that all stations' vicinities in New Taipei received the treatments of both events. Nevertheless, for any period τ in the event window, $\Delta \ln MA_n^{E1} \times T_\tau$ and $\Delta \ln MA_n^{E2} \times T_\tau$ have a nearly perfect correlation greater than 0.99. One is a proxy for the other.

Therefore, we can specify the following model to test the parallel trend:

$$\ln P_{idnt} = \beta_0 + \sum_{\tau=\underline{\tau}}^{\tau_{E1}-2} \varphi_\tau \Delta ln CMA_n^{Ek} \times T_\tau + \sum_{\tau=\tau_{E1}}^{\tau_{E2}-1} \varphi_\tau \Delta \ln CMA_n^{E1} \times T_\tau + \sum_{\tau=\tau_{E2}}^{\bar{\tau}} \varphi_\tau \Delta \ln CMA_n^{E2} \times T_\tau + X_{idnt}\psi + Z_{idnt}\gamma + MRT_{1200} \times MRT_n\, \mu_{1200,n} + \delta_d + \theta_t + \varepsilon_{idnt}, \qquad \forall k = 1, 2 \tag{5}$$

which applies the same two-way clustered standard errors as Eq. (4). Event time is substituted for calendar time for T_τ and θ_t; hence, the model does not have the two post-treatment indicator variables T_{after}^{E1} and T_{after}^{E2}. Each quarterly event time indicator variable T_τ within the event window $[\underline{\tau}, \overline{\tau}]$ is interacted with the corresponding log CMA change variable, with $\tau = \tau_{E1}\text{-}1$ being the base period. The parallel trend is valid if $\hat{\varphi}_\tau$ statistically equals to zero, $\forall\ \tau < \tau_{E1}\text{-}1$. For robustness, we perform two regressions: the pre-E1-treatment indicators interact with $\Delta\ln MA_n^{E1}$ in one and $\Delta\ln MA_n^{E2}$ in the other.

4.4 Conversion from Housing Prices into Land Values

The hedonic regression of Eq. (4) decomposes housing prices into the multiplications of the implicit prices and quantities of the properties' observable features. The detailed housing characteristics in our sample enable satisfactory appraisals of the homes' physical structures. Thus, we can subtract the value of the housing structure $X_{idnt}\hat{\psi}$ from the transacted price $\ln P_{idnt}$ to uncover the associated land value $\ln V_{idnt}$ for every property:

$$\ln V_{idnt} = \ln P_{idnt} - X_{idnt}\hat{\psi}, \qquad \forall i \tag{6}$$

Eqs. (4) and (6) convey the following notions. First, improved commuter market access $\Delta\ln CMA_n$ of a metro station upon the transit system expansion may increase housing prices in the station's vicinity. Second, the increased price of any property is due to the appreciation in the value of the associated land and is independent of the structure value—a point made clear by the classical monocentric city model. Thus, $\hat{\beta}_{DD}^{Ek} = \frac{\partial \ln V_{idnt}}{\partial \Delta\ln MA_n^{Ek} \times T_{after}}, \forall k = 1{,}2$; the DD estimates of the treatment effects on housing prices can be carried over to the impacts on land value.

We take the average of $\ln V_{idnt}$ by year and detailed location. The locations are delineated by the interaction of three sets of location dummy variables, on which $District_d$, MRT_n, and MRT_{1200} are vectors of the district, nearest metro station, and proximity to station indicator variables, respectively. The interaction creates a total number of 95 locations. To prevent influence from the lumpiness of average land values in areas with few property transactions, we drop locations with less than 5 transactions in any year between 2013 and 2019. With this filter, 71 locations remain.

Having a panel of locational annual average land values $\ln V_{ldn,t}$, we then look into the building level construction permits and find the project start date of each building and the number of homes and gross floor area (m^2) the building can provide upon completion. We aggregate the information to derive the total number of housing units and gross floor area launched in each location and year.

Locations may not have new projects launched every year, as project launches are infrequent events. Therefore, for every location-year observation with zero units and gross floor area launched, we replace the number with 1 to facilitate logarithmic transformation. The above data processing procedure leads to a balanced panel covering 71 locations in New Taipei and 7 years from 2013 to 2019.

4.5 IV Tobit Regression for Housing Production

The inquiry central to this research is whether public transport system expansion in the central city (i.e., Taipei City) can motivate developers to launch new housing projects in commutable suburbs (i.e., New Taipei City). To contextualize developers' decisions for profit maximization, we shall incorporate several important aspects into the empirical analysis. These aspects are discussed after the introduction of regression functions for ease of elaboration.

The deliberation leads to the following IV Tobit model, in which the first stage regression is:

$$\begin{aligned}\ln V_{ldn,t} = \beta_0 + \beta_1 \ln V_{ldn,t-1} + \beta_2 \Delta \ln CMA_n^{E1} \times T_{after}^{E1} + \beta_3 \Delta \ln CMA_n^{E2} \times T_{after}^{E2} \\ + \beta_4 \ln \sigma_{d,t} + \beta_5 MRT_{1200} + \rho_n + \delta_d + \theta_t + \varepsilon_{ldn,t}\end{aligned} \tag{7}$$

and the second stage regression is:

$$\begin{gathered}\ln HQ_{ldn,t}^{*} = \alpha_0 + \alpha_1 \ln V_{ldn,t} + a_2 \ln \sigma_{d,t} + a_3 MRT_{1200} + \rho_n + \delta_d + \theta_t + \xi_{ldn,t} \\ s.t. \quad \ln HQ_{ldn,t} = \begin{cases} 0 & \text{if } \ln HQ_{ldn,t}^{*} \leq 0 \\ \ln HQ_{ldn,t}^{*} & \text{if } \ln HQ_{ldn,t}^{*} > 0 \end{cases}\end{gathered} \tag{8}$$

In this system of equations comprising Eqs. (7) and (8), $\ln V_{ldn,t}$ is the average land value of the locale l in district d at year t with the nearest metro station being n, and $\ln HQ_{ldn,t}$ is the quantity of new housing construction at the locale initiated in year t. The regressions include four vectors of fixed effects, including the proximity to metro station fixed effect MRT_{1200}, the nearest metro station fixed effects ρ_n, the district fixed effects δ_d, and the year fixed effects θ_t.

The variable $\ln\sigma_{d,t}$ concerns the district-level house price volatility, and its construction procedure is as follows. We first slice every month into two for the entire sample period to create bi-weekly time dummy variables. The next step produces district-level bi-weekly housing price indices $\hat{\eta}_{d,\iota}$, $\forall d,\iota$ through a hedonic pricing regression that includes the interactions between the district fixed effects and bi-weekly time fixed effects.[10] The bi-weekly price change, then, is $\Delta\hat{\eta}_{d,\iota} = \hat{\eta}_{d,\iota} - \hat{\eta}_{d,\iota-1}$, $\forall d,\iota$. Subsequently, for each district d and year t, we obtain $\sigma_{d,t}$, the standard deviation of the district's bi-weekly price changes in years t and $t+1$. The standard deviation of high-frequency price changes is the conventional definition of volatility, and the incorporation of price changes in year $t+1$ into the calculation reflects developers' forward-looking nature.

[10] The regression for the price index construction takes the form: $ln\, P_{idnt} = \beta_0 + X_{idnt}\psi + Z_{idnt}\gamma + MRT_{1200} \times MRT_n\, \mu_{1200,n} + District_d \delta_d + District_d \times Biweek_t \eta_{dt} + \varepsilon_{idnt}$. The vector of estimates $\hat{\eta}_{dt}$ constitutes the district-level bi-weekly price indices.

Lastly, the explanatory variables included in Eq. (7) but excluded in Eq. (8) are $\ln V_{ldn,t-1}$, $\Delta\ln CMA_n^{E1} \times T_{after}^{E1}$, and $\Delta\ln CMA_n^{E2} \times T_{after}^{E2}$. The first variable is the one-year lagged average land value of the locale, and the other two variables relate to the cumulative CMA improvement upon the corresponding metro-line opening event. These variables are the instruments for $\ln V_{ldnt}$ in the IV Tobit model.

The above IV Tobit model for the supplied quantity of new housing incorporates the following aspects of economics. First, contextualizing lands as real options is necessary for examining and answering what motivates developers to launch new housing projects. Like many world's major cities, lands are freehold in the Taipei metropolis. The local governments are not "big governments" that can outlaw land banking, and developers have the right to keep their lands vacant until the optimal time for development.

The real-option theory is matured and intensively used in the real estate literature of land development. Well-received works include McDonald and Siegel (1986), Capozza and Helsley (1990), and Bulan et al. (2009), to name a few. Particularly, Lu et al. (2020) presented a coherent theoretical framework and put it into the context of New Taipei City for empirical analysis of real estate developments there, emphasizing the parameters of consideration from the developers' viewpoint. Among the extant studies, two principles are universal: Higher expected return shortens the time in the land bank, but greater uncertainty prolongs it.

In other words, a locale will feature a higher quantity of new housing construction being initiated if developers foresee higher expected returns (Murphy, 2018). On the contrary, the new housing construction will be less if developers project more market uncertainty. In the context of our panel data regression, the variables $\ln V_{ldn,t}$ and $\ln\sigma_{d,t}$ of Eq. (8) reflect the return and uncertainty that developers face in expected profit maximization.

Location features also influence time to development; Capozza and Helsley (1990) proved this point through theory, and Lu et al. (2020) substantiated it with empirical evidence on New Taipei City. Therefore, Eq. (8) controls all static location features, whether observable or unobservable, through the three sets of location fixed effects, namely MRT_{1200}, ρ_n, δ_d, that together give the complete delineations of locations in the panel data.

Costs matter, speaking about returns. As Glaeser and Gyourko (2018) suggested, the development costs of housing production comprise three elements: the construction cost, the land acquisition cost, and a rate of entrepreneurial profit, which we interpret as the developer's opportunity cost to devote resources to a project. As they explained, when land value exceeds development costs, an abnormal return, an incentive for project launch, appears; this is the situation that the quantity implication of real options theory would apply.

However, new housing construction can be completely absent from locales. Glaeser and Gyourko (2018) asserted that when the land value falls below development costs, developers holding the lands will not launch new projects, and the observed quantity of new housing is zero. Their assertion features in our panel data; the observations with zero housing production are around 50%. Thus, we adopt the Tobit model.

The discussion so far has made clear that Eq. (8) is the supply-side function of new housing construction. Eq. (7) relates to the demand side because the regressand is uncovered from the micro-level hedonic pricing that predicts households' willingness to pay for land features owing to derived demand. Besides the lagged value commonly used as an instrument in panel data analysis, it is also appropriate to exclude CMA-related variables from Eq. (8) but include them in Eq. (7) as additional instruments. In essence, convenient access to many popular places from the locale is what home buyers care about and will to pay for it. That convenience's relationship to new housing construction is indirect. Ultimately, developers' motivation to launch new projects is about the land value they can extract from home buyers, and their Lagrangian for profit maximization per se does not have a place for CMA. Furthermore, the CMA changes arose from sophisticated topological reconfigurations of stations and tracks in the network, and this research examines locales distant from where the metro lines were placed. Through the network-mediated spillover effect in an inconsequential places approach, desirable exogeneity is embedded in the CMA changes (see Jing and Liao (2023) for detailed explanations).

5. Results and Analyses

This section presents the estimation results and delves into the causal effects of Taipei City's metro transit expansion on New Taipei's housing development. The analysis addresses two points. One is the impact of CMA on housing prices, and the other is the response of housing production to land values.

5.1 Descriptive Statistics

Table 3 presents the summary statistics, names, and definitions of variables used in DD regressions, except for the time and location fixed effect dummy variables, and the summary statistics are for the sample period from 2013.01 to 2016.12. The average housing price was NT$12.5 million (≈US$400k) in the 11 districts of New Taipei. The station-specific CMA changes $\Delta \ln CMA_n^{E1}$ average 7% upon Xinyi Line's opening (November 2013) from the original CMA levels, and the changes $\Delta \ln CMA_n^{E2}$ average 13% upon Shongshane Line's opening (November 2014) from those original levels before Xinyi Line's operation.

[Insert Table 3 Here]

Table 4 exhibits the housing price ln(Price) and metro-station proximity status MRT_{1200}'s correlation coefficients with other explanatory variables. The correlations with the price are usually substantial. On the other hand, the correlations with MRT_{1200} are modest or minimal; the coefficients are all less than 0.11 and the large majority fall below 0.06 in absolute value. Since the metro stations have no notable correlations with housing and locational characteristics that can be evidenced, the selection of treatment is not a matter of first-order importance.

[Insert Table 4 Here]

5.2 CMA Treatment Effect

The following two tables examine the treatment effect of commuter market access (CMA) induced by Xinyi and Songshan Line openings. Table 5 presents DD regression results. For brevity, it only reports the DD estimates; the full results are in Table A1. Column (4) uses the preferred model specification identical to Eq. (4), while other columns facilitate comparisons. $\hat{\beta}_{DD}^{E2}$ and its standard errors are highly consistent and statistically the same across all columns, and the R^2 values are almost identical. The $\hat{\beta}_{DD}^{E1}$ coefficient is statistically the same whether controlling district fixed effects, although it is slightly larger, more significant, and precise without that control. Similarly, $\hat{\beta}_{DD}^{E1}$ is statistically the same whether using year-quarter or year-month fixed effects, although the latter gives slightly more precision. The comparison between Columns (4) and (5) also shows that the choice between the two- and one-way clustered standard errors makes little difference.

[Insert Table 5 Here]

Table 5 also performs the t-test for $\beta_{DD}^{E1} = \beta_{DD}^{E2}$. The two DD parameters are statistically identical in all five regressions. Because $\Delta \ln CMA_n^{E2} \geq \Delta \ln CMA_n^{E1}$, $\forall n$, the finding that $\beta_{DD}^{E1} = \beta_{DD}^{E2}$ implies no heterogeneous response in treatment intensity. Hence, the average causal response of the treated to CMA (a continuous treatment variable) is identified according to Callaway (2021). The homogeneous response in treatment intensity is also consistent with the finding of Jing and Liao (2023), who examined the CMA of Singapore's metro transit.

Having accepted the homogeneous response hypothesis (constant slope effect), we perform the constrained regression with $\beta_{DD}^{E1} = \beta_{DD}^{E2}$, and Table 6 shows the results. Except for this equality constraint, the model specification strictly follows Eq. (4). Column (1) applies the same sample period as Table 5, and the next three columns each extend the period by one additional year. The CMA DD coefficient estimate and its standard errors are highly stable regardless of the sample length.

[Insert Table 6 Here]

On average, a 1% improvement in commuter market access (CMA) can increase housing prices by 0.33%, and this finding is statistically significant at the 5% level. Property values notably increased in distant suburbs with metro transit services due to the network-mediated spillover effect (Jing and Liao, 2023) arising from the metro system expansion in the central city of Taipei metropolis. Because the expansion incorporated several popular destinations of workplaces (e.g., Taipei 101) and entertainment hubs (e.g., Taipei Arena) in Taipei City into the system coverage, commuter market access considerably improved in the distant suburbs of New Taipei. The findings from this analysis and Jing and Liao (2023) suggest that the network-mediated spillover effect has external validity as it exists in various world's major cities.

5.3 Parallel Trend

Figure 4 presents $\hat{\varphi}_\tau$ coefficient estimates and their corresponding 95% confidence intervals resulted from the two event studies, which adopt the specification of Eq. (5) and apply the sample from 2013Q1 to 2016Q4. Panel A exhibits the one using $\Delta \ln MA_n^{E1} \times T_\tau$ for the pre-treatment quarters, and Panel B shows the other using $\Delta \ln MA_n^{E2} \times T_\tau$ for those quarters, to confirm result robustness. Quarterly event time is substituted for the calendar time; and the opening dates of Xinyi and Songshan lines mark the beginning of the E1 and E2 quarters, respectively. The two panels of results are almost identical due to nearly perfect correlation between $\Delta \ln MA_n^{E1} \times T_\tau$ and $\Delta \ln MA_n^{E2} \times T_\tau$ $\forall \tau$.

[Insert Figure 4 Here]

The results suggest that φ_τ is not different from 0 during pre-treatment times, and the parallel trend assumption is valid. On the contrary, φ_τ is generally positive and usually significant after the first event. An improved CMA level can cause higher housing prices for homes in proximity to the metro station. These findings are further supported by the supplementary Figure A1, which exhibits the event studies that use the same model specification but extend the sample period to 2019Q4.

5.4 Parameter Insensitivity

The CMA formula (Eq. 1) comprises a power-decay parameter λ, which intuitively reflects usefulness of metro transit services. Commuting time does not matter when $\lambda \to 0$. However, when $\lambda \to \infty$, any distance of commute exhausts commuters completely, and metro transit is useless. By continuity, households' marginal willingness to pay for CMA should diminish when λ is sufficiently large, and Jing and Liao (2023) evidenced this pattern. Thus, we test the sensitivity of our results to the choice of the λ value.

Table 7 exhibits $\hat{\beta}_{DD}^{E1}$ and $\hat{\beta}_{DD}^{E2}$ from the baseline and constrained DD regressions of Eq. (4) for a wide range of λ from 0.1 to 2.5, in which 0.3 is the benchmark calibrated from the literature and used throughout this paper's analysis. The model specification is intentical to the fourth column of either Table 5 or 6. The coefficient estimates and significance levels are stable, and they only decline when λ is empirically implausibly large.

[Insert Table 7 Here]

5.5 Transit-Oriented New Housing Launches in New Taipei

The above analysis evidences that the Xinyi and Songshan lines, which connected notable employment centers and entertainment hubs in Taipei City, have improved commuter market access (CMA) in distant suburbs with metro services in New Taipei. Brought by this transit network expansion in the central city, the greater convenience to access popular destinations stimulates home prices in those commutable surburbs, and the willingness to pay for the homes increases in the CMA level of convenience. The higher property values can motivate developers to launch new housing projects in those suburbs in theory, and the remaining analysis presents empirical evidences.

As explained in the methodology section, developers take their lands as real options, and their development decisions are guided by the land values and associated volatility. New housing construction can be completely absent in neighborhoods, as lands are freehold and land banking is lawful. These behavioral natures of developers are incorporated into the following analysis that applies the IV Tobit model (Eqs. 7 and 8) and the compiled neighborhood annual panel data.

Table 8 reports summary statistics for neighborhood-level variables in the panel dataset, which is a balanced panel with 71 neighborhoods from 2013 to 2019. The two variables ln*HQ* and ln*GFA*—the log numbers of new housing units and gross floor areas launched in the neighborhood during the year—measure the quantity of new housing construction. The variable ln*Value* is the neighborhood average land value uncovered through hedonic pricing, and *Volatility* is the standard deviation of biweekly price changes in the district consisting the neighborhood during the current year and the year after. Lastly, MRT_{1200} indicates whether the neighborhood is within 1.2 km to a metro station in New Taipei.

[Insert Table 8 Here]

Table 9 presents the results of the supplied quantity regression (Eq. 8) of IV Tobit. The three sets of location fixed effect—MRT_{1200}, $\mathrm{MRT}_{\mathrm{n}}$ FEs, and District FEs—comprehensively control time-invariant unobservables that vary across the delineated neighborhoods. Since the two-way clustering of standard errors is technically infeasible, we test several kinds of standard errors to enhance robustness, including the district-level clustering in Column (2), $\mathrm{MRT}_{1200}\times\mathrm{MRT}_{\mathrm{n}}$-level clustering in Column (3), and bootstrap standard errors with 500 replications in Column (4). The main results are robust across the different specifications.

[Insert Table 9 Here]

The table illustrates two sets of findings. First, the results are consistent with the real-option theory. Increased land values imply a higher return motivating developers to shorten their wait, and those reaching the optimal timing launch projects resulting in new housing construction observed in the neighborhood. On the other hand, increased price volatility of lands implies uncertainty making developers to wait longer and reduces new housing construction.

The second-set findings are the main results. Firstly, neighborhoods with convenient public transportation are places with more new-housing launches. Outside the central city of Taipei metropolis, annual housing construction was 2.26% more in terms of housing units in neighborhoods with metro-station access than those without the services.

More importantly, the transit network expansion in Tapei City, the central city, improved the CMA, increased land values, and caused a greater quantity of new housing construction in New Taipei City's neighborhoods with the metro services. On average, a 1% improvement in commuter market access caused a significant 2.47% increase (0.33×7.49) in the annual number of new housing units launched.

Table 10 reports the results of regressions using the same specification as their Table 9's counterparts but replacing the gross floor areas of new housing construction as the dependent variable. The findings from Table 9 remain robust. In New Taipei, annual housing construction was 4.00% more in gross floor areas in the neighborhoods with the metro services. On average, a 1% better CMA caused a 3.76% increase (0.33×11.38) in the annual gross floor housing areas launched.

[Insert Table 10 Here]

6. Conclusion and Policy Recommendation

This paper demonstrates that metro-transit network expansion in the central city can induce a network mediated spillover effect that improves the CMA (commuter market access), increases housing prices and land values, and incentivizes developers to launch new housing projects in distant commutable suburbs. As a result, the supplied housing quanitity can increase in these areas with the metro transit services, allowing households who have economic ties in the fully built-up central city to access more affordable housing without being stretch commuters.

The research studies the case of the Taipei metropolis in which Taipei City, a classical superstar city in Asia, is the central city. Difference-in-differences and IV Tobit analyses investigate housing demand and supply. The completions of the Xinyi and Songshan lines, which service Taipei City's prime areas and incorporate many popular workplace or entertainment destinations into the metro transit system, have pervasively improved CMA outside the Tapei City. For every 1% better CMA, home values grew by 0.33% and annual housing construction increased by 2.26% in housing units and 4.00% more in GFA on average in the suburbs with metro station access. Because new housing construction constitutes a part of the housing stock supply, the empirical findings suggest that the network-mediated spillover effect in tandem with the CMA improvements resulted from the transit network expansion would have increased housing supply elasticity and improved housing affordability to an extent. This implication is coherent with the slowly gradually improving price-to-income ratios in Table 2.

The study draws the conclusion that public transport network expansion can be an effective policy instrument to support transit-oriented urban development and improve housing affordability in superstar cities. The policy can shape an "all-win" situation for local governments, households, and private developers.

The government of a superstar city typically enjoys strong public finance, but it faces the challenging housing affordability issue that bothers the city's key workers and young professionals, especially if the city is already fully built. The tension could trigger the divide in society and instability in governance. The superstar city government can invest in metro transit and create a convenient public transportation system, and the initial emphasis should go beyond providing transit services within the city, for otherwise, the investment would only exacerbate the superstar city problem. The investment should also focus on creating commutable surburbs in satellite cities or commuting towns in the superstar city's greater metropolitan area. Subsequently, the superstar city government can expand the transit system to incorporate additional popular destinations, whether for work or entertainment, within its city. The expansion can then create a network-mediated spillover effect that improves the commuter market access of all metro stations including those in suburban satellite cities and commuter towns. Thus, the favorable residential locations this expansion shapes are not limited to those within the superstar city.

Residential land values can increase in commutable surburbs outside the superstar city but serviced by the metro transit because the system expansion improves commuter market access there and households value this convenience. The higher land value can motivate profit-maximizing developers to launch new housing projects in those commutable suburbs, thereby increasing the total housing quantity supplied in the metropolitan area. The new constructions bring corporate profits to the developers.

Households, who find the necessity housing too expensive in the superstar city but have or want to have economic ties there, now have the opportunities to live in the commutable surburbs without being stretch commuters. Local housing prices do increase in these suburbs after the metro system expansion. However, the appreciation is justifiable because it is grounded on more convenient metro transit for the households, and private developers do need that incentive to increase the supplied housing quantity. At the metropolitan level, housing affordability can improve for the households with economic ties in the superstar city because housing supply becomes more elastic through the public transport development. The metro transit expansion brings benefits to the demand and supply sides of housing to support sustainable housing development.

Residential density can rise in the commutable surburbs after new housing projects' completions. The metro transit expansion that incorporates additional popular destinations in the central city makes the commutable surburbs more attractive and supports a higher density there. The increased residential density near suburban metro stations enhances financial sustainability of the metro transit operator. The mutually reinforcing process between the transit supply and demand can support transit-oriented development and reduce private-vehicle reliance to foster sustainable urban development.

Local governments of the satellite cities and commuting towns can also gain, even though the fiscal benefits of public transit revenues may belong to the superstar city's government. Their public finance and their capacity in public goods provision can improve because the greater housing quantity and higher prices can bring them more property tax revenues. In sum, sucn an all-win policy outcome favors sustainable development of real estate, public transportation, and cities.

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Table 1. Taipei City Households' Mortgage Burden, 2013-2019

	Mortgage Payment to Income Ratio (MPIR)
2013Q4	63%
2014Q4	67%
2015Q5	66%
2016Q4	62%
2017Q4	62%
2018Q4	57%
2019Q4	57%

Notes: The MPIR figures were published by the Ministry of the Interior. The algorithm to derive an MPIR is as follows. First, the monthly principal and interest payments are computed using a 20-year equal amortization method and a loan-to-value ratio of 70%. Then, the resulting amount is divided by households' median monthly disposable income to obtain the ratio.

Table 2. Housing Affordability to the Taipei City's Median-Income Household

Panel A: **Taipei City housing**: price/income ratio of Taipei City's median-income household					
	$P_{10\%}$	$P_{25\%}$	$P_{50\%}$	$P_{75\%}$	$P_{90\%}$
2013	5.69	9.10	14.93	24.58	41.88
2014	5.75	9.29	14.77	25.03	41.57
2015	5.27	8.79	14.50	24.69	41.73
2016	6.00	9.23	14.25	23.30	38.09
2017	5.73	8.82	14.10	23.71	40.11
2018	5.70	9.14	13.84	23.07	38.67
2019	5.62	8.83	13.49	21.92	35.65
Panel B: **New Taipei City housing in Taipei Basin**: price/income ratio of Taipei City's median-income household					
	$P_{10\%}$	$P_{25\%}$	$P_{50\%}$	$P_{75\%}$	$P_{90\%}$
2013	5.46	7.28	10.74	15.93	23.85
2014	5.75	7.61	11.05	16.63	23.79
2015	5.62	7.56	10.63	15.81	23.90
2016	5.83	7.71	10.93	15.95	23.39
2017	5.73	7.62	10.58	15.87	23.10
2018	5.60	7.30	10.40	15.27	22.23
2019	5.34	6.95	10.04	14.45	21.28

Notes: The price-to-income ratio is the housing price at the given percentile divided by the median-income household's disposable income. The source for the percentile price calculation is the Real Price Registration System, from which we obtained transaction data for the entire Taipei City and the 11 districts of New Taipei within the Tapei Basin. The median household's disposable incomes are from the Taipei Department of Budget, Accounting, and Statistics. The notation $P_{k\%}$ stands for the k-th percentile.

Table 3. Summary Statistics

Description	Variables	Obs.	Mean	S.D.
Dependent variable				
Log total transaction price	$\ln Price$	63,779	16.34	0.59
Housing characteristics				
Size of the unit (km^2)	Size	63,779	124.80	97.69
Age of the unit	Age	63,779	15.39	13.79
Floor level of the unit	Floor	63,779	7.47	5.77
Number of rooms	#Room	63,779	4.30	1.57
Total number of floors of the building	Total floors	63,778	13.21	8.04
(=1) if a new sale; (=0) if not	New sale	63,779	0.28	0.45
(=1) if with parking space; (=0) if not	Carpark	63,779	0.40	0.49
Locale characteristics				
(=1) if in a lawful residential zone; (=0) if not	Residential	63,779	0.80	0.40
Distance to Taipei Main Station (km)	TPS dist.	63,779	10.80	3.06
Distance to the nearest highway (km)	Hwy. dist.	63,779	0.82	0.64
Distance to the nearest park (km)	Park dist.	63,779	0.27	0.17
Distance to the nearest bus stop (km)	Bus dist.	63,468	0.48	0.24
Treatment and time indicator				
(=1) if $\leq$ 1.2km to metro station; (=0) if not	MRT_{1200}	63,779	0.78	0.42
(=1) if the transaction occurred between the two events; (=0) if not	T_{after}^{E1}	63,779	0.21	0.40
(=1) if the transaction occurred after the second event; (=0) if not	T_{after}^{E2}	63,779	0.43	0.50
Station-level CMA in New Taipei City				
CMA change upon Xinyi Line opening	$\Delta \ln CMA_n^{E1}$	35	0.07	0.003
CMA change upon Songshan Line opening	$\Delta \ln CMA_n^{E2}$	35	0.13	0.005

Notes: Summary statistics are presented for variables, including the house price, housing characteristics, locational features, and station-level commuter market access changes used in the DD regressions, except for the fixed effects. Also included are the variables' names and definitions.

Table 4. Correlation Coefficients

	$\ln Price$	MRT_{1200}
$\ln Price$	1	
MRT_{1200}	-0.012	1
Size	0.697	-0.079
#Room	0.356	-0.033
Floor	0.339	0.013
New sale	0.365	-0.045
Age	-0.532	0.038
Carpark	0.630	-0.082
Total floor	0.463	0.021
Residential	-0.061	-0.062
TPS dist.	-0.034	-0.060
Park dist.	-0.019	-0.016
Hwy. dist.	-0.002	-0.059
Bus dist.	-0.067	0.107

Notes: This table presents $\ln Price$ and MRT_{1200}'s correlation coefficients with other housing characteristics and locational features.

Table 5. DD Regression

D.V.	(1) $\ln Price$	(2) $\ln Price$	(3) $\ln Price$	(4) $\ln Price$	(5) $\ln Price$
$\Delta \ln CMA_n^{E1} \times T_{after}^{E1}$	0.60**	0.53*	0.57**	0.51*	0.51*
	(0.25)	(0.27)	(0.23)	(0.25)	(0.26)
$\Delta \ln CMA_n^{E2} \times T_{after}^{E2}$	0.33**	0.34**	0.32**	0.33**	0.33**
	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)
t-test			$H_0: \beta_{DD}^{E1} = \beta_{DD}^{E2}$		
p-value	0.12	0.31	0.12	0.32	0.37
Constant term	Y	Y	Y	Y	Y
Housing characteristics	Y	Y	Y	Y	Y
Locale characteristics	Y	Y	Y	Y	Y
Post-treatment indicators	Y	Y	Y	Y	Y
$MRT_{1200} \times MRT_n$ FEs	Y	Y	Y	Y	Y
District FEs	-	Y	-	Y	Y
Year-Month FEs	-	-	Y	Y	Y
Year-Quarter FEs	Y	Y	-	-	-
Clustered S.E.	2-way	2-way	2-way	2-way	1-way
Observations	63,464	63,464	63,464	63,464	63,464
R^2	0.83	0.83	0.83	0.84	0.84

Notes: This table presents the results of DD regressions (Eq. 4), which use the 2013.01-2016.12 sample. It only reports the estimates of key variables for brevity; full results are in Table A1. The labels "Y" and "-" indicate the inclusion and omission of the variables, respectively. Standard errors are clustered two ways at the levels of District FEs and $MRT_{1200} \times MRT_n$ FEs in Columns 1-4 and one way at the level of $MRT_{1200} \times MRT_n$ FEs in Column 5. The asterisk marks *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 6. Constrained Regression

	(1)	(2)	(3)	(4)
	Constrained condition: $\beta_{DD}^{E1} = \beta_{DD}^{E2}$			
Sample period	2013.01-2016.12	2013.01-2017.12	2013.01-2018.12	2013.01-2019.12
D.V.	$\ln Price$	$\ln Price$	$\ln Price$	$\ln Price$
$\Delta \ln CMA_n^{E1} \times T_{after}^{E1}$	0.33**	0.33**	0.32**	0.33**
	(0.14)	(0.13)	(0.13)	(0.13)
$\Delta \ln CMA_n^{E2} \times T_{after}^{E2}$	0.33**	0.33**	0.32**	0.33**
	(0.14)	(0.13)	(0.13)	(0.13)
Housing characteristics	Y	Y	Y	Y
Locale characteristics	Y	Y	Y	Y
Post-treatment indicators	Y	Y	Y	Y
$MRT_{1200} \times MRT_n$ FEs	Y	Y	Y	Y
District FEs	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y
Observations	63,467	78,616	92,578	108,475

Notes: This table presents constrained regressions with the condition $\beta_{DD}^{E1} = \beta_{DD}^{E2}$. Except for this equality constraint, the specification is identical to Table 5's Column 5. Standard errors are clustered one way by the $MRT_{1200} \times MRT_n$ grouping for methodological feasibility. The asterisk marks *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 7. Parameter Sensitivity Test

λ	0.1	0.2	**0.3**	0.4	0.5	1	1.5	2	2.5
					Panel A. Baseline DD				
$\Delta\ln CMA_n^{E1} \times T_{after}^{E1}$	0.50*	0.51*	0.51*	0.51*	0.51*	0.50**	0.39**	0.22**	0.12*
	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)	(0.22)	(0.12)	(0.08)	(0.06)
$\Delta\ln CMA_n^{E2} \times T_{after}^{E2}$	0.31**	0.32**	0.33**	0.34**	0.35**	0.39***	0.38**	0.25*	0.14
	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.11)
					Panel B. Constrained Regression				
$\Delta\ln CMA_n^{E1} \times T_{after}^{E1}$	0.31**	0.32**	0.33**	0.33**	0.34**	0.37***	0.36***	0.24*	0.14
	(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.10)
$\Delta\ln CMA_n^{E2} \times T_{after}^{E2}$	0.31**	0.32**	0.33**	0.33**	0.34**	0.37***	0.36***	0.24*	0.14
	(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.10)

Notes: This table shows that the $\hat{\beta}_{DD}^{E1}$ and $\hat{\beta}_{DD}^{E2}$ estimates are insensitive to the value of λ in Eq. (1). The benchmark value used in all other regressions is $\lambda = 0.3$. Panels A and B use the same specification as Table 5's Column 4 and Table 6's Column 4, respectively. The asterisk marks *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Table 8. Summary Statistics: Neighborhood Annual Panel Data

Description	Variable	N	mean	sd
Log new housing units launched	$\ln HQ$	497	2.11	2.43
Log new gross floor areas launched	$\ln GFA$	497	4.47	4.74
Log average land value	$\ln Value$	497	15.52	0.16
District-level price volatility (see Sec. 4.5)	Volatility	497	0.06	0.03
(=1) if $\leq$ 1.2km to metro station; (=0) if not	MRT_{1200}	497	0.56	0.50

Note: This table tabulates the names, definitions, and summary statistics of the variables used in the IV Tobit regressions. The variables of log CMA changes are in Table 3, and the fixed effects are unreported for brevity. The dataset is a balanced annual panel with 71 neighborhoods from 2013-2019.

Table 9. Annual Housing Production: Number of New Units Launched

D.V.	(1) $\ln HQ$	(2) $\ln HQ$	(3) $\ln HQ$	(4) $\ln HQ$
$\ln\widehat{Value}$	7.49***	7.49***	7.49**	7.49**
	(2.87)	(2.44)	(3.80)	(3.17)
Volatility	-13.73	-13.73**	-13.73	-13.73
	(12.30)	(5.51)	(11.66)	(13.04)
MRT_{1200}	2.26***	2.26***	2.26***	2.26***
	(0.49)	(0.52)	(0.63)	(0.53)
Constant	-114.31**	-114.31***	-114.31*	-114.31**
	(44.67)	(38.02)	(59.15)	(49.61)
MRT_n FEs	Y	Y	Y	Y
District FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Observations	426	426	426	426
Pseudo R^2	0.16	0.16	0.16	0.16
Clustered S.E.	-	District	$MRT_{1200}\times MRT_n$	-
Bootstrap S.E.	-	-	-	500 rep.

Notes: This table presents the second-stage results of IV Tobit regression for which the instruments are the lagged lnValue, $\Delta\ln CMA_n^{E1}$ and $\Delta\ln CMA_n^{E2}$. The asterisk marks *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. Clustered standard errors are in one-way clustering for methodological feasibility.

Table 10. Annual Housing Production: New Gross Floor Areas Launched

D.V.	(1) $\ln GFA$	(2) $\ln GFA$	(3) $\ln GFA$	(4) $\ln GFA$
$\ln\widehat{Value}$	11.38**	11.38**	11.38*	11.38*
	(5.26)	(5.40)	(6.78)	(5.82)
Volatility	-23.65	-23.65**	-23.65	-23.65
	(23.27)	(10.95)	(22.75)	(25.06)
MRT_{1200}	4.00***	4.00***	4.00***	4.00***
	(0.93)	(1.23)	(1.18)	(1.00)
Constant	-170.76**	-170.76**	-170.76	-170.76*
	(81.69)	(83.54)	(105.48)	(90.91)
MRT_n FEs	Y	Y	Y	Y
District FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Observations	426	426	426	426
Pseudo R^2	0.14	0.14	0.14	0.14
Clustered S.E.	-	District	$MRT_{1200}\times MRT_n$	-
Bootstrap S.E.	-	-	-	500 rep.

Notes: This table presents the second-stage results of IV Tobit regression for which the instruments are the lagged lnValue, $\Delta\ln CMA_n^{E1}$ and $\Delta\ln CMA_n^{E2}$. The asterisk marks *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. Clustered standard errors are in one-way clustering for methodological feasibility.

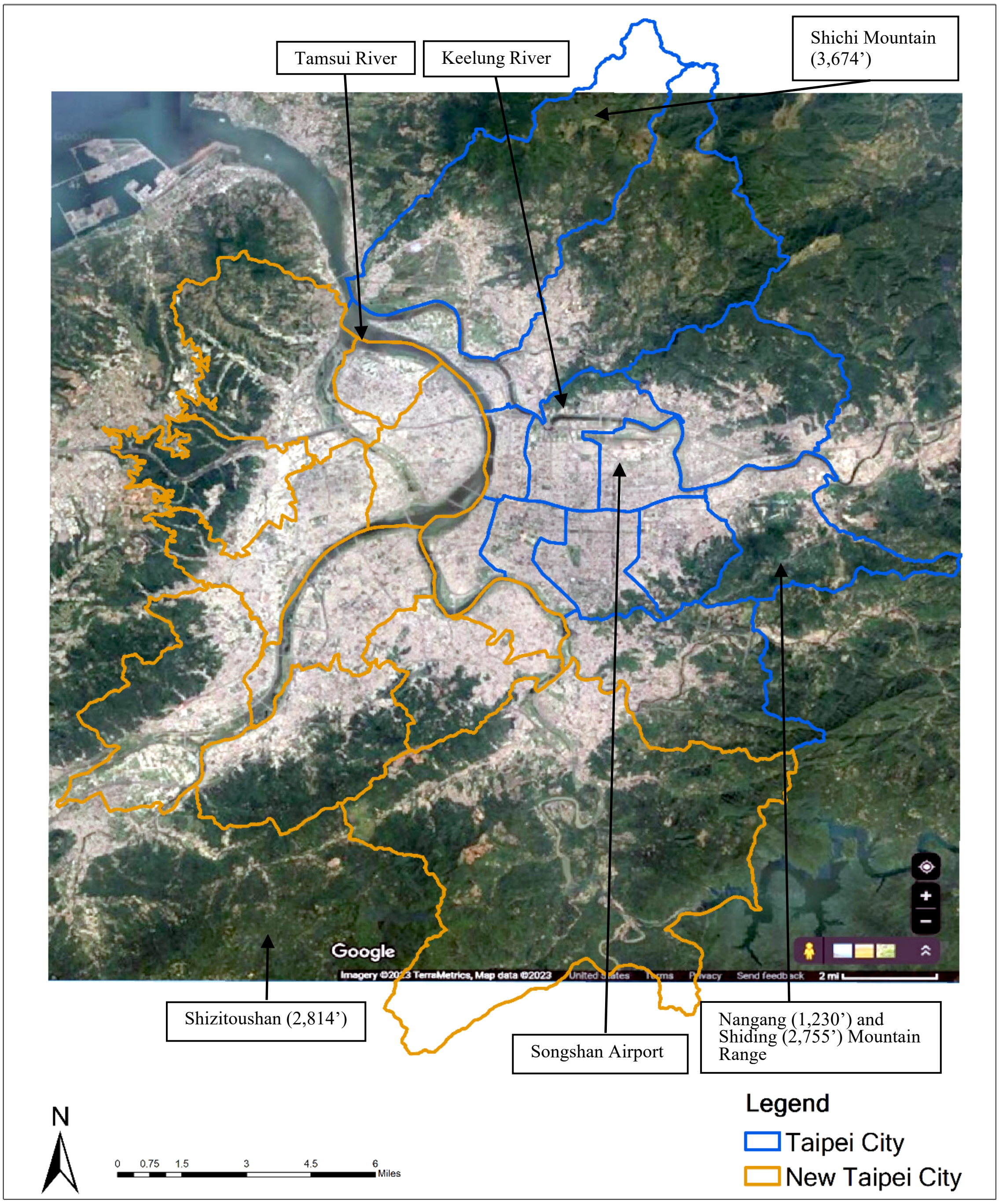


Figure 1. Geographic Constraints of Taipei City

Notes: This satellite map exhibits the geographic constraints of the Taipei Metropolis situated in the Taipei Basin. Taipei City is in the east part of the basin and comprises 12 districts marked by blue lines, and New Taipei City is in the west, including 11 districts marked by amber lines. The mountains (with peak elevation), rivers, and the airport, which restrict Taipei City's housing supply, are pointed out in the map.

Figure 2. Taipei Metro System

Notes: This figure includes Taipei Metro's year 2015 system map. The network comprises five major lines, namely the Brown Line (Wenhu Line), Red Line (Tamsui-Xinyi Line), Green Line (Songshan-Xindian Line), Amber Line (Zhonghe-Xinlu Line), and Blue Line (Banna Line). The added black dashed lines distinguish between metro stations in Taipei City and New Taipei City. The Xinyi and Songshan lines are annotated by white dashes. Xinyi Line is the Red Line's segment from the Chiang Kai-Shek Memorial Hall to the Xiangshan station. Songshan line is the Green Line's segment operated between the Ximen and Songshan stations.

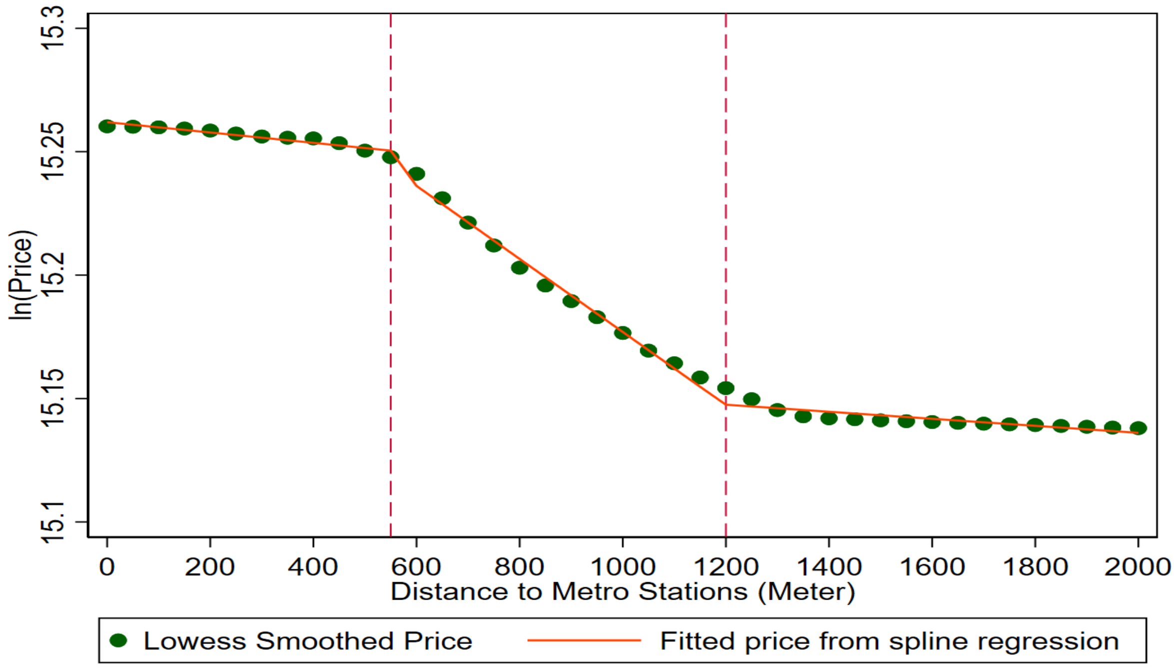
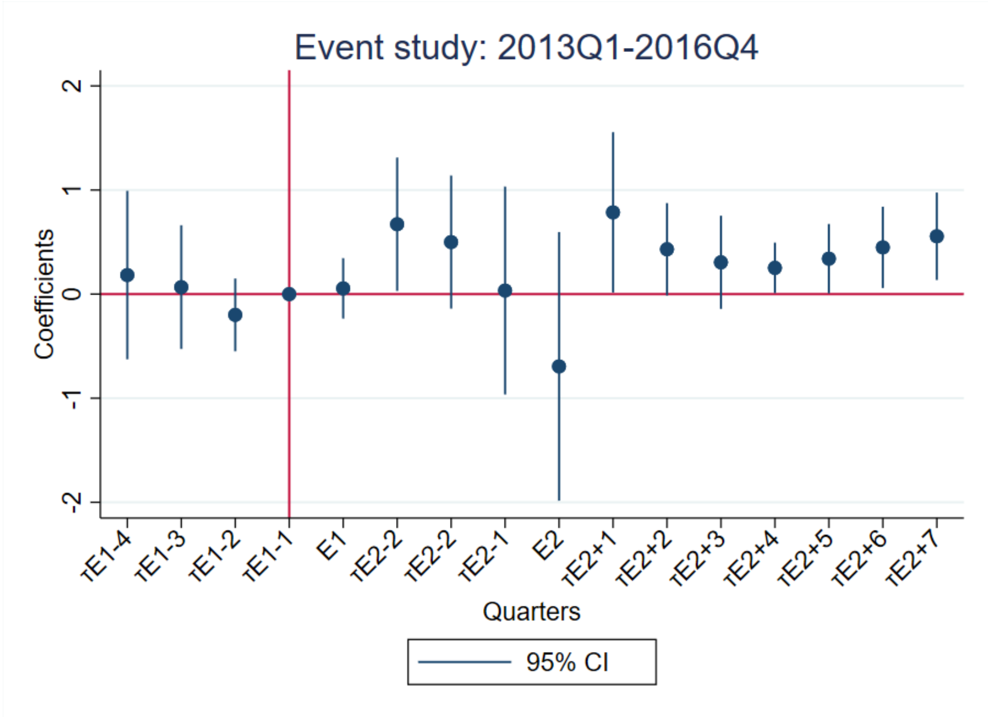


Figure 3. Housing Price Gradient of Distance to Metro Stations

Notes: The figure visualizes the housing price gradient in the distance to the nearest MRT station from the locally weighted scatterplot smoothing (the green connected dots) and the best-fit spline regression with 550m and 1200m being the knots (the kinked orange line). The bandwidth for the smoothing is 0.6.

Panel A. Pre-trend treatment intensity: $\Delta \ln CMA_n^{E1}$



Panel B. Pre-trend treatment intensity: $\Delta \ln CMA_n^{E2}$

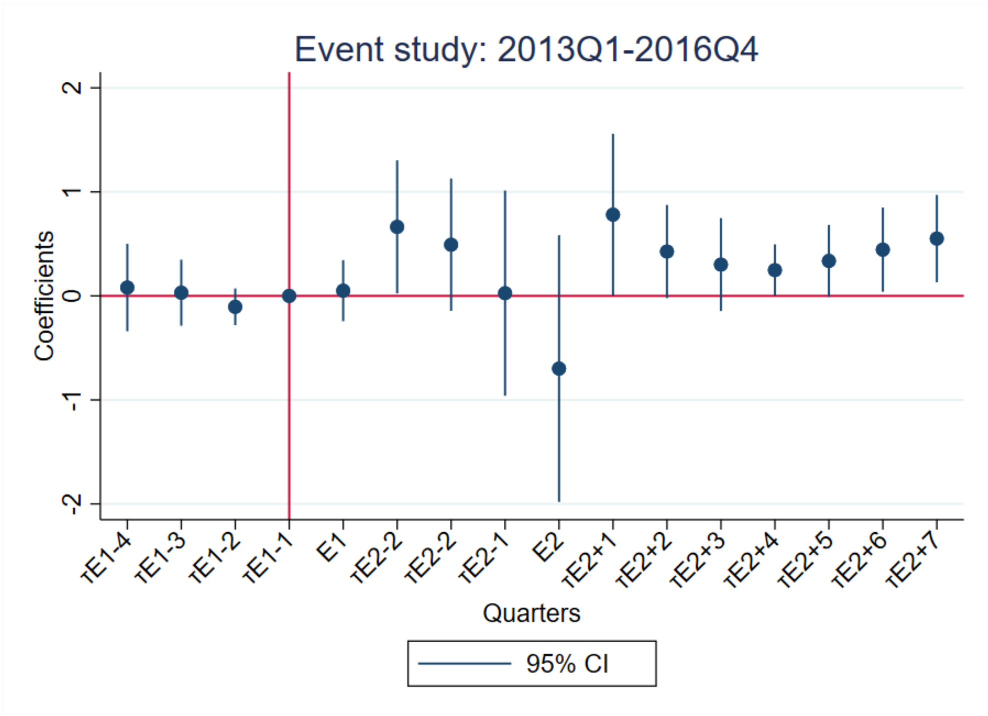


Figure 4. Event study

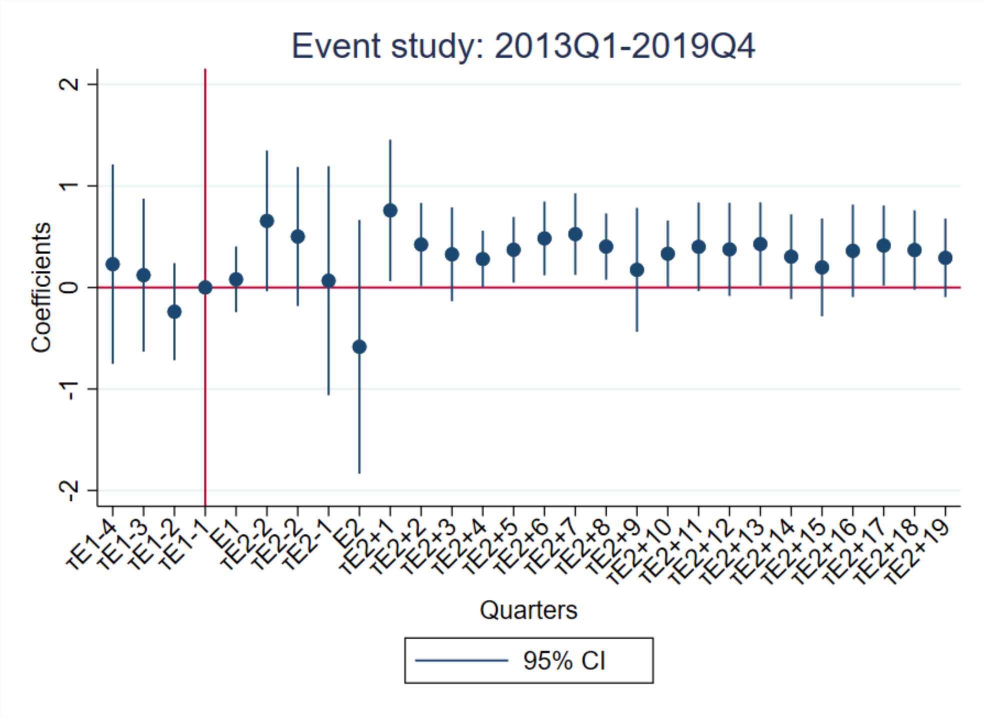
Notes: This event study figure applies the sample from 2013Q1 to 2016Q4. Quarterly event time is substituted for the calendar time; and the opening dates of Xinyi and Songshan lines mark the beginning of the E1 and E2 quarters, respectively. The treatment intensity variable imposed for the pretreatment period is $\Delta \ln CMA_n^{E1}$ for Panel A and $\Delta \ln CMA_n^{E2}$ for Panel B.

Table A1. Baseline DD regression: Full results

D.V.	(1) ln$Price$	(2) ln$Price$	(3) ln$Price$	(4) ln$Price$	(5) ln$Price$
$\Delta\ln CMA_n^{E1} \times T_{after}^{E1}$	0.60**	0.53*	0.57**	0.51*	0.51*
	(0.25)	(0.27)	(0.23)	(0.25)	(0.26)
$\Delta\ln CMA_n^{E2} \times T_{after}^{E2}$	0.33**	0.34**	0.32**	0.33**	0.33**
	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)
T_{after}^{E1}	-0.03*	-0.03	-0.04	-0.04	-0.04
	(0.01)	(0.02)	(0.03)	(0.03)	(0.04)
T_{after}^{E2}	-0.03	-0.03	-0.04	-0.04	-0.04
	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)
Size	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Size^2$	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
#Room	0.09***	0.09***	0.09***	0.09***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\#Room^2$	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Floor	-0.01**	-0.01***	-0.01**	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Floor^2$	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
New sale	-0.03	-0.03	-0.03	-0.03	-0.03
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Age	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age^2	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Carpark	0.06*	0.06*	0.06*	0.06*	0.06**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Total floor	0.01**	0.01**	0.01**	0.01**	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total $floor^2$	-0.00*	-0.00*	-0.00*	-0.00**	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Residential	0.04**	0.04***	0.03**	0.04***	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
TPS dist.	-0.03**	-0.03**	-0.03**	-0.03**	-0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Park dist.	-0.05	-0.07	-0.05	-0.07	-0.07
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Hwy. dist.	-0.01	-0.02	-0.01	-0.01	-0.01
	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)
Bus dist.	-0.10**	-0.09**	-0.10**	-0.09**	-0.09***
	(0.04)	(0.04)	(0.04)	(0.03)	(0.02)
Constant	15.88***	15.96***	15.87***	15.95***	15.95***
	(0.13)	(0.17)	(0.13)	(0.17)	(0.16)
$MRT_{1200}{\times}MRT_n$ FEs	Y	Y	Y	Y	Y
District FEs	-	Y	-	Y	Y
Year-Month FEs	-	-	Y	Y	Y
Year-Quarter FEs	Y	Y	-	-	-
Clustered S.E.	2-way	2-way	2-way	2-way	1-way
Observations	63,464	63,464	63,464	63,464	63,464
R-squared	0.83	0.83	0.83	0.84	0.84

Notes: This table exhibits the full results of DD regressions (Eq. 4) presented in Table 5. The labels "Y" and "-" indicate the inclusion and omission of the variables, respectively. Standard errors are clustered two ways at the levels of District FEs and $MRT_{1200}{\times}MRT_n$ FEs in Columns 1-4 and one way at the level of $MRT_{1200}{\times}MRT_n$ FEs in Column 5. The asterisk marks *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Panel A. Pre-trend treatment intensity: $\Delta \ln CMA_n^{E1}$



Panel B. Pre-trend treatment intensity: $\Delta \ln CMA_n^{E2}$

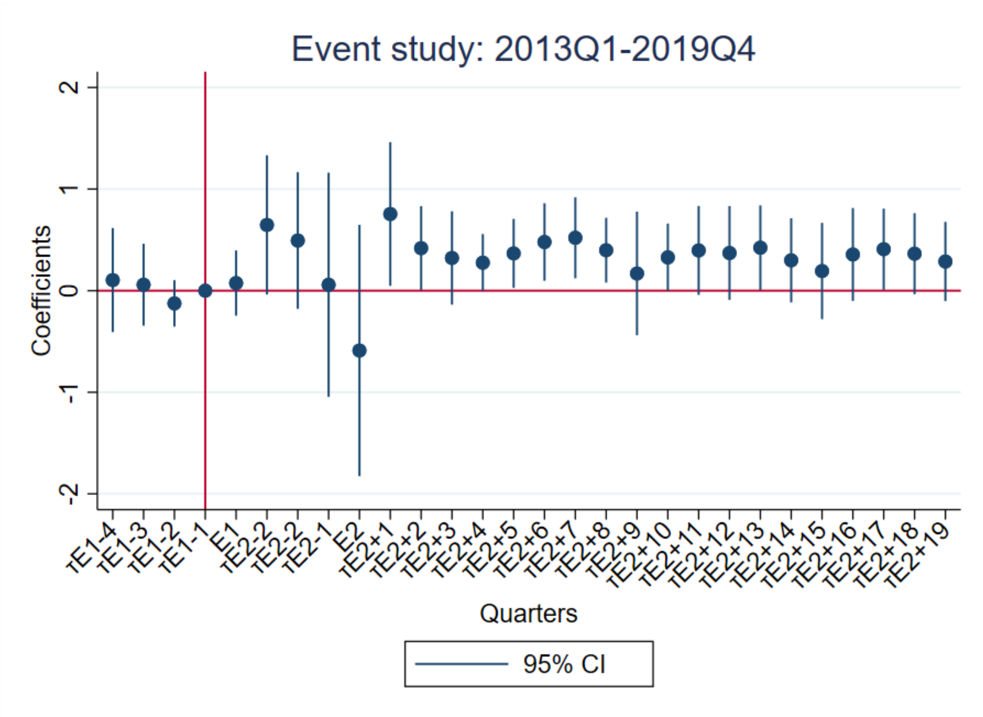


Figure A1. Event study: 2013Q1 - 2019Q4

Notes: This event study figure applies the sample from 2013Q1 to 2019Q4. Quarterly event time is substituted for the calendar time; and the opening dates of Xinyi and Songshan lines mark the beginning of the E1 and E2 quarters, respectively. The treatment intensity variable imposed for the pretreatment period is $\Delta \ln CMA_n^{E1}$ for Panel A and $\Delta \ln CMA_n^{E2}$ for Panel B.