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Gravity Model for Intra-metropolitan Mobility–A Case Study of Taipei Metropolitan Areas
都會區內居住遷移之重力模型研究—以台北都會區為例

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ABSTRACT

Previous research has largely focused on macro-level regional migration or micro-level residential mobility, neglecting the meso-level dynamics of mobility and destination choices within urban districts. To fill the research gap, this study examines the determinants of intra-metropolitan residential mobility within the framework of a gravity model. The empirical results yield several noteworthy findings by using the panel data from 30 districts within the Taipei metropolitan areas (TMA) spanning from 2009 to 2021. Firstly, the determinants of intra-metropolitan residential mobility, such as population, distance impedance, housing prices, and housing supply contribute to the attractiveness of each district. Secondly, migrants exhibit a tendency to relocate to destinations with a larger mass (attractiveness) relative to their original residential area. Thirdly, population agglomeration and housing prices of districts emerge as pivotal factors influencing residential mobility, whereas the impact of housing supply appears comparatively subdued. These findings provide valuable insights for local administrations in formulating housing policies and calculating mobility trends when rezoning new development areas. Additionally, it offers guidance to land developers in crafting effective marketing strategies to navigate competitive market dynamics.

Key words: Gravity Model, Intra-metropolitan Mobility, Residential Mobility, Housing Price, Population Agglomeration

摘　要

以往研究聚焦於宏觀面之區域遷移或微觀面的居住遷移，然忽略城市內之遷移與地點選擇的動態。本研究採用重力模型為框架，探討都會區內居住遷移之因素。以2009年至2021年間台北都會區30個行政區的縱橫資料為基礎，實證結果發現。1.人口、距離阻抗、房價與住宅供給構成各行政區吸引力的因素。2.遷移者傾向搬遷至相較原居住區具更大吸引力的目的地。3.人口聚集與住宅價格為影響住宅遷移的關鍵因素，而住宅供給影響較弱。這些發現為地方政府在制定住宅政策與重新劃定開發區時預測遷移趨勢提供參考。同時，也為土地開發商設計有效的行銷策略提供指引。

關鍵詞：重力模型、都會區內遷移、住宅遷移、住宅價格、人口聚集

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1. Introduction

Housing crises have long been a persistent challenge for many countries, affecting an estimated 1.6 billion people by 2025 (Garemo et al., 2014). In many industrialized nations, aging populations and population decline have emerged as pressing societal issues, leading to a significant decrease in housing demand. In light of these demographic changes, local governments face the question of how effective urban sprawl is as a policy tool, particularly given constrained funding. These policies often become costly and time-consuming due to suburbanization, limited funds, and residents' reluctance to relocate, thus failing to resolve the housing crisis (Bardhan et al., 2011). While aging populations and emerging trends like remote work pose broader challenges to housing demand, this study focuses on key quantifiable determinants—population, housing prices, supply, and distance—to model intra-metropolitan mobility, with other factors reserved for future exploration.

In the realm of population migration, two main types are commonly distinguished: regional migration and residential mobility. Regional migration refers to individuals moving to minimize spatial costs while maximizing economic opportunities (Zabel, 2012; Molloy et al., 2017). In contrast, residential mobility, the focus of this paper, is driven by considerations of livability across the household life-course, defined here as the perceived quality and suitability of a residential environment influencing mobility decisions (Pacione, 1990; Ruth & Franklin, 2014; Peng & Tsai, 2019). It is primarily influenced by factors like the relative quality and cost of living, social networks, personal circumstances, and housing affordability (Ermisch & Washbrook, 2012; Peng & Tsai, 2019). While much research has explored the reasons and processes behind residential relocation, there is a notable gap in examining mobility patterns within the context of housing market dynamics and competition.

The questions of "Where to move?" and "How to choose?" are central to the study of residential mobility. These decisions are impacted by various factors, including household characteristics, economic opportunities, amenities, accessibility, and affordability (Ermisch & Washbrook, 2012; Peng & Tsai, 2019). This paper addresses three key questions: 1) What factors affect and contribute to the attractiveness of a district? That feedback to "where to move?" 2) How does residential mobility intersect with spatial housing markets? Feedback back to "how to choose?" 3) What differences exist in residential mobility between core areas and fringe areas? To address these, we propose applying the "gravity model" to residential mobility, analogous to Reilly's law of gravitation (Reilly, 1929), which explains why individuals prefer larger malls. Similarly, residential mobility thus reflects people's tendency to relocate in pursuit of enhanced livability.

Using the Taipei metropolitan areas (TMA) as a case study, this research analyzes data from 30 districts spanning 2009 to 2021 through panel data analysis. (Note. 1) In this study, the core areas refer to Taipei City (TC), while the fringe areas encompass New Taipei City (NTC), providing a clear spatial distinction for examining intra-metropolitan mobility. The outcomes of this study are anticipated to yield valuable insights for both local administrations and real estate developers.

Understanding mobility patterns and the interactions among districts can assist local administrations in policy-making for urban development initiatives. For real estate developers, comprehending these patterns and employing a suitable model to identify potential customers and competitors for new projects can facilitate the formulation of enhanced pricing and promotion strategies.

The subsequent sections of this paper are structured as follows: Section 2 offers a comprehensive literature review on urban mobility, Section 3 delineates the research design, scope, empirical data, and empirical model, Section 4 presents the findings of our analysis and provides in-depth discussions, and finally, Section 5 draws conclusions from the study's outcomes.

2. Literature Review

2.1 Gravity Model

Researchers have primarily employed quantitative methods to capture population migration patterns, with the gravity, radiation, and intervening opportunities models emerging as the major methodologies for simulation analysis in this domain.

Zipf (1946) introduced the concept of the law of gravitation from physics to explain the sway of distance on population migration, leading to the development of the gravity model. This model provides a simplistic yet insightful framework for understanding migration patterns and has been widely utilized in population migration research (Haynes & Fotheringham, 1990; Zhao et al., 2021). Moreover, the model has found applications in diverse fields such as transportation, geography, regional economics, and retailing (Wilson, 1971; Scott, 2017; Levine et. al., 2019).

The intervening opportunities model, introduced by Stouffer (1940), posits that population migration is powered by the number of intervening opportunities between the origin and destination, rather than solely by distance. While this model does not specify the exact considerations of origin and destination, it remains valuable for comparative analyses with the gravity model, with researches demonstrating similar results between the two (Barbosa et al., 2018; Niu, 2022). Despite this, the gravity model continues to be popular for further research (de Dios & Willumsen, 2011; Niu, 2022).

The radiation model, introduced by Simini et al. (2012), addresses limitations of the gravity and intervening opportunities models by incorporating distance decay effects. Unlike the point-to-point nature of the gravity model, the radiation model considers two steps towards destination selection: weighting geographical candidates based on opportunities and sorting by distance. While this model does not require parameter calibration, it may be less applicable at other scales without adjustments. Subsequent researches have introduced elasticity coefficients to enhance the model's applicability (Simini et al., 2013; Bettencourt, 2021).

Common determinants in these models include socioeconomic characteristics and population distribution, categorized as either positive (numerator) or negative effects (denominator) in the gravity model. Positive effects describe a district's attractiveness (e.g., neighborhood, quality, housing availability), while negative effects describe obstacles or exclusiveness (e.g., distance, travel time, housing prices). Differences among these models lie in variable preferences and model formulations (Barbosa et al., 2018; Li et al., 2021). According to the gravity theory, each district exhibits both positive (attraction) and negative (repulsion) effects on residential mobility in urban areas, though these effects remain to be fully elucidated.

2.2 Metropolitan Mobility and Determinants

Metropolitan Mobility

Metropolitan mobility, as discussed in urban economic, refers to household relocation within cities, allowing adjustments in housing consumption throughout the life cycle (Deimantas, 2023). Research on micro-level relocation links mobility to household attributes, life-cycle events, job changes, income fluctuations, and education (Clark, 2013; Chang, 2013; Guo et al., 2020).

Population

Population size refers to the total number of permanent residents in a given area, and is closely tied to urbanization, economic development, public services, and local policies Population size refers to the total number of permanent residents in a given area and is influenced by urbanization, economic development, public services, quality of life, and local policies (Lemoine-Rodríguez et. al., 2020; Turok et. al., 2021)

As cities grow and develop economically, they often form urban agglomerations where neighboring cities collaborate and share functions, driving spatially connected development (Arribas-Bel & Sanz-Gravia, 2014). However, this growth also brings challenges such as rising density, congestion, high living costs, declining fertility, and environmental issues, leading to population outflows (Oishi & Schimmack, 2010; Turok et al., 2021; Skakkebæk et al., 2022). Large populations enhance regional cohesion and attractiveness, creating a self-reinforcing cycle of migration (Fang & Yu, 2017). Research shows that highly educated immigrants tend to remain in core urban areas, adding economic value but also impacting land use (Wang & Wang, 2017; You et al., 2018). Population distribution shifts through aggregation and diffusion mechanisms, shaping urban spatial dynamics (Wang & Wang, 2017; He et al., 2019).

Conversely, people's understanding of a city is often limited to familiar surroundings, creating a perception space that provides comfort and security. Within this space, individuals rely on known information and social connections, shaping their mobility behaviors (Lalli, 1992; Hay, 1998; Devine-Wright & Lyons, 1997; Jorgensen & Stedman, 2001). Familiarity with a local area shapes mobility behaviors within a city, reinforcing the "neighborhood effect," where proximity provides a sense of security and encourages localized movement. Venturing beyond requires acquiring additional information, influencing relocation decisions. (Oishi & Schimmack, 2010; Gustafson, 2014; Clark, 2020; Wu et al., 2024).

Furthermore, income significantly constrains housing choices, as households tend to relocate within neighborhoods of similar economic status (Clark, 2020). Whether reflected in housing prices or rental costs, financial capacity shapes mobility behavior (Lee et al., 2000; Baker, 2016; Li et al., 2021). While some move up or down the socioeconomic scale, most transitions occur within comparable economic contexts (Chen & Peng, 2024).

Housing Availability

Housing availability influences intra-urban relocation, as households adjust their housing consumption based on space, location, amenities, and quality (Strassmann, 1991; Dieleman et al., 2000; Van Ommeren & Van Leuvensteijn, 2005). Urban residents frequently move to newer or larger homes to improve living conditions, with mobility patterns shaped by housing supply dynamics, including tenure structure, housing types, land-use regulations, and geographical features (Van der Vlist et al., 2002; Lee & Waddell, 2010). Furthermore, research indicates that the introduction of new dwellings into the market stimulates residential mobility (Peng et al., 2009; Peng & Tsai, 2019). However, such upgrades typically come with increased costs, prompting households to minimize expenses by relocating, despite potential rises in transportation costs (Hua, 2001; Li et al., 2021). This dynamic adjustment of housing consumption to market conditions underscores the significance of housing market factors in intra-urban relocations, as highlighted by various researchers (Dieleman, 2001; Chen & Peng, 2024).

Housing Price

Housing market structures influence prices, creating affordability challenges that drive relocation decisions (Lee et al., 2000; Baker, 2016). Studies show that many households moving to outer areas are young first-time buyers prioritizing affordability (Lin, 2021). High housing prices increase living costs, discouraging migration to expensive areas (Lin, 2021). Additionally, rising housing costs indirectly inflate goods prices by increasing commercial rents (Liu, 2015). Overall, research suggests a negative correlation between high housing prices and migration, shaped by simultaneity and spatial interdependence (Chen & Peng, 2024).

Finally, we aim to integrate the aforementioned determinants into our Intra-Urban Mobility Gravity Model (IUMGM), incorporating Reilly's law and residential mobility concepts, utilizing the Taipei metropolitan areas (TMA) as a case study. The administrative structure of TMA influences government funding and policy priorities, with Taipei City, the capital and a special municipality since 1949, contrasting with New Taipei City, which was upgraded in 2007 and fully encircles Taipei. Their combined economic output of 9.53 trillion NT dollars for Taipei and 4.78 trillion NT dollars for New Taipei. (Note. 2) According to the report Urban and Regional Development Statistics, the Taipei metropolitan areas (TMA) cover just 6% of Taiwan's land area but houses nearly 30% of its population. Data from the Real Estate Information Platform further indicated that TMA consistently records the nation's highest housing prices and accounts for 30% of Taiwan's residential housing stock and housing transactions over the past decade.

3. Research Design

In the early 20th century, researchers endeavored to develop and refine gravity models to better capture patterns of mobility. Reilly (1929) applied the gravity model to analyze retail markets. Amidst these gravity model implementations, the development of the IUMGM can be delineated into three key steps: evaluating determinants pertinent to the mobility gravity model, assessing distance impedance, and formulating the mobility model itself, and our hypotheses are formed as follow.

3.1 The Model

There are various gravity models derived from substantial research, which can be categorized based on the types of information they provide (Haynes & Fotheringham, 2020). The foundational model is based on the concept of the attraction-constrained gravity model proposed by Wilson (1971), shown as Eq. (1). V_i represents a vector of origin attributes; W_j represents a vector of destination attributes; S_{ij} represents a vector of separation attributes, and interaction between any pair of regions is specified as T_{ij}.

$$T_{ij} = f(V_i, W_j, S_{ij}) \quad (1)$$

In accordance with the law of gravity, we assume that each administrative district exhibits a distinct mass (attractiveness) for residential mobility, influenced by four key factors: population agglomeration, housing prices, housing supply, and distance impedance (Fang & Yu, 2017). It is hypothesized that migrants will tend to relocate preferentially to destinations with greater attractiveness, signifying a gravitational pull toward districts with higher attractiveness. Conversely, districts with lesser attractiveness are expected to experience lower levels of residential mobility. Furthermore, residential mobility primarily aims to enhance living standards, aligning with Reilly's (1929) conceptualization. The ultimate selection of a relocation destination involves a comparative evaluation of districts and their housing markets, considering residents' financial capabilities. Consequently, the ratios of district attractiveness emerge as a result of these shared factors.

Therefore, we have modified the Eq. (1) with adding the above factors into Eq. (2). With Eq. (2), PMT_{ij} is the proportion of migrants to District j who are from Taipei City i to represent both T_{ij}, and V_i. as they share the same vector of origin attributes. DP, HS, HP represent the district's population, the housing Supply, and housing price are respectively. (Note. 3) These three determinants are found to be strongly affecting residential mobility and are also represented as the vector of destination attributes W_j, and finally D refers to district impedance as the vector of separation attribute S_{ij}. α is the scale parameter and, a1, a2, a3 and a4 are the parameters to be estimated.

$$PMT_{ij} = \alpha DP_j^{a1} HS_j^{a2} HP_j^{a3} D_{ij}^{a4} \quad (2)$$

Furthermore, to understand the influence of each determinant, we combine them into Eq. (2) and present it in logarithmic form on Eq. (3). The logarithmic transformation of the model reveals how each determinant affects mobility. We assume that housing price emerges as a pivotal determinant, exerting a significant negative effect on mobility, and holds the greatest influence in shaping residential mobility patterns. Conversely, population demonstrates a positive impact, attracting individuals towards relocation. In contrast, housing market dynamics appear to have the least influence on mobility within the model.

$$\log PMT_{ij} = \log\alpha + a1 \log DP_j + a2 \log HS_j + a3 \log HP_j + a4 \log D_{ij} + \varepsilon_{it} \quad (3)$$

In distinguishing between the core areas (Taipei City) and suburban areas (New Taipei City), we propose that the weighting of determinants influencing mobility patterns shifts slightly. Specifically, within Taipei City, population is perceived to have the greatest impact on individuals' relocation decisions. However, in New Taipei City, housing price becomes a more influential determinant in shaping residential mobility decisions.

According to gravity theory, mobility is influenced by distance, a concept that also applies to residential mobility, which tends to occur over shorter distances and is often shaped by social networks or neighborhood effects. (Jorgensen & Stedman, 2001; Oishi & Schimmack, 2010; Gustafson, 2014; Zhao et al., 2021). Consequently, greater impedance effects result in lower residential mobility. The distance impedance function is typically specified as a negative exponential function, which previous research has demonstrated to be the most effective among simple monotonic forms. In our model, the measurement of distance between districts and central areas uses the 'center of population' of the regions. (Note. 4) The center of population is a geographical point that represents the central point of a region's population. With the application of GIS, we can capture the geometric median, which is the point that minimizes the sum of distances to all individuals in the population (or equivalently, minimizes the average distance).

The study employs panel-data analysis for 30 districts in the TMA (Taipei City and New Taipei City), Taiwan, spanning from 2009 to 2021. This method offers the advantage of expanding the sample data by incorporating both cross-sectional and time-series dimensions. The benefit is that panel data can observe the individual-specific effect without the time effect (time-invariance) and can include items such as race, gender, and unidentified characteristics of households. There are three scenarios as follows: simple linear regression, which can be implemented with a pooled model, the fixed-effects model (FEM), and the random-effects model (REM). The LM (Lagrange Multiplier) test is a test for the REM based on the OLS residual (Breusch and Pagan, 1980), and Hausman (1978) introduced a method to test for the REM or FEM. The FEM rejects the null hypothesis of the test but the REM accepts it, which we will examine.

3.2 Data Sources and Summary of Taipei metropolitan areas

Two platforms provide the major sources of the mobility data to our study which are the vital registration of the household statistics of the Taipei City (TC) and New Taipei City (NTC) statistical database, and the "Real Estate Information Platform" of the Ministry of the Interior. (Note. 5) Figure 1 illustrates the spatial distribution of districts' housing prices in TMA, categorizing them into six distinct regions. (Note. 6) Figure 2 presents the map of the Taipei metropolitan areas (TMA), highlighting its main transportation systems. The proportion of migrants (PMT) from Taipei City is calculated by the number of migrants from Taipei City divided by the Taipei City population. The purpose of this ratio is to serve as the indicator of the attractiveness of each district to citizens in Taipei City. The above independent variables and the forecast influences are summarized in Table 1.

3.3 Descriptive Statistics

Table 2 and Figure 3 present the summary statistics for two cities and 30 districts; Firstly, analyzing the proportion of migrants from Taipei City (PMT) across districts reveals interesting trends. Specifically, PMT for TC (0.857%) is lower than that for NTC (1.694%). Moreover, the deviation indicates each district's or area's attractiveness in terms of mobility, which can be linked to our four determinants. TC (0.085%) exhibits a smaller deviation compared to NTC (0.229%), suggesting that NTC may possess greater appeal for residents relocating from Taipei City. Delving deeper into specific regions and districts, TC_HHP and NTC_HHP stand out as having the highest PMT occupation rates, exceeding 0.130% among the 30 districts. Furthermore, the deviation among these districts tends to be larger, indicating significant disparities in attractiveness for mobility.

Table 1 Definition of Factors and Variables

Factors	Variables	Definition	Sources	Exp Sign
Dependent Variables				
Proportion of Migrants from Taipei City	PMT	The number of migrants from Taipei City to the district / the population of Taipei City	Taipei City & New Taipei City Statistical Database and Author Calculation	
Independent Variables				
Distance	D	The distance between the Center of population in each district and the center of population in Taipei City	Taipei City & New Taipei City Statistical Database and Author Calculation	-
Population	DP	The number of populations in each district	Taipei City & New Taipei City Statistical Database	+
Housing Price	HP	The average housing price in each district	Real Estate Information Platform	-
Housing Supply	HS	The number of new dwelling within 5 years in each district	Same as Above	+
Gravity Mass	GM	The ratio of Distance, Population, Housing price and Housing Supply	Author Calculation	+/-

Note: 1. PMT: Proportion of Migrants from Taipei City. For districts within Taipei City, the proportion is calculated as the number of migrants moving from other districts in Taipei City to the target district; D: Distance between District and Taipei City; DP: Population; HP: Housing Price; HS: Housing Supply; GM: Gravity Mass. 2. Compiled and organized by the author

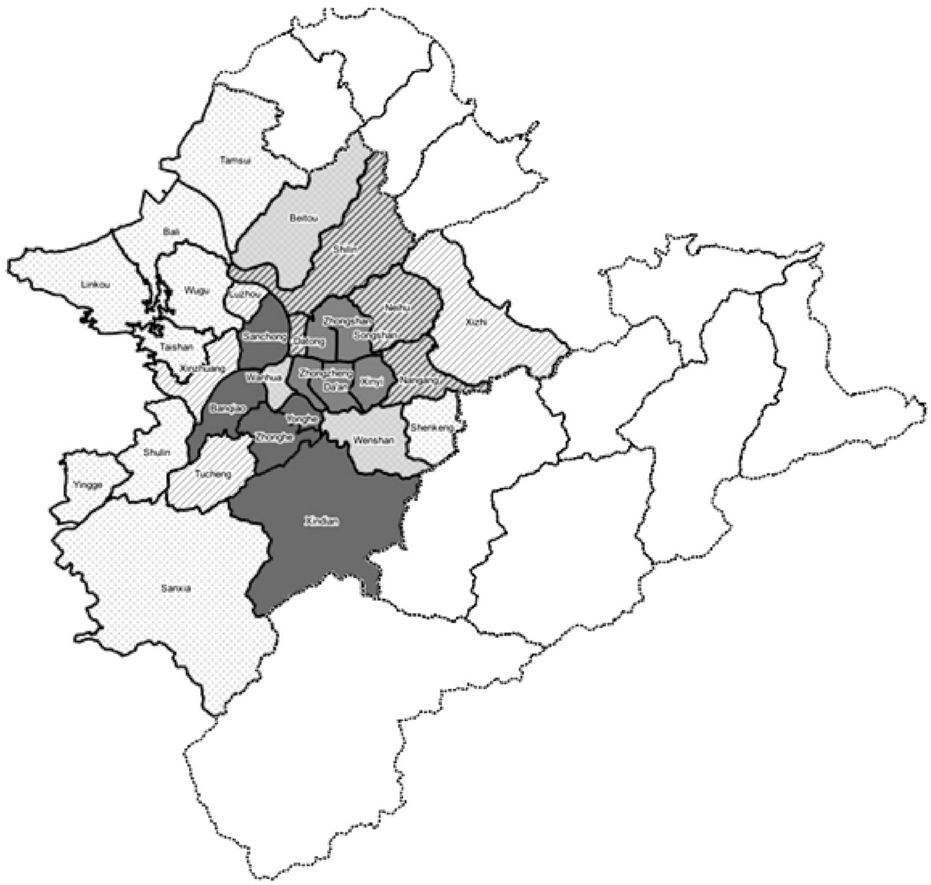

Figure 1 Spatial Distribution of Districts' Housing Prices in the Taipei Metropolitan Area

Note: 1. According to the Cathy Real Estate Price Index, the figure illustrates the housing price range across six regions within the Taipei metropolitan areas. The districts in Taipei City are represented in red, while those in New Taipei City are shown in blue. The districts in black dot lines are the rural areas in New Taipei City, which not included in this study. The central area, depicted in solid dark red (corresponding to TC_HHP), represents districts with the highest housing prices in Taipei City, reflecting significant residential demand and economic activity; followed by areas in hashed medium red (TC_MHP) indicating median housing prices, and hashed X with light red (TC_LHP) representing lower housing prices within Taipei City. Similarly, the dark blue regions (NTC_HHP) indicate the highest housing prices in New Taipei City, while the hashed medium blue (NTC_MHP) and the hashed X with light blue (NTC_LHP) regions correspond to median and lower housing prices, respectively. 2. Source from: https://www.cathay-red.com.tw/tw/About/House, compiled and organized by the author.

Secondly, the distances are measured from the center of population in the Taipei City (TC). We chose this approach to capture the average distance between citizens in each district and the TC, thus representing the barrier for migrants in residential mobility. Interestingly, from Table 2, the statistics reveal that TC_HHP is closest to the TC's center of population. Notably, the deviation is larger for NTC_LHP and TC_MHP. This is typically attributed to the establishment of new and large development areas in these regions, thus leading to the increased population.

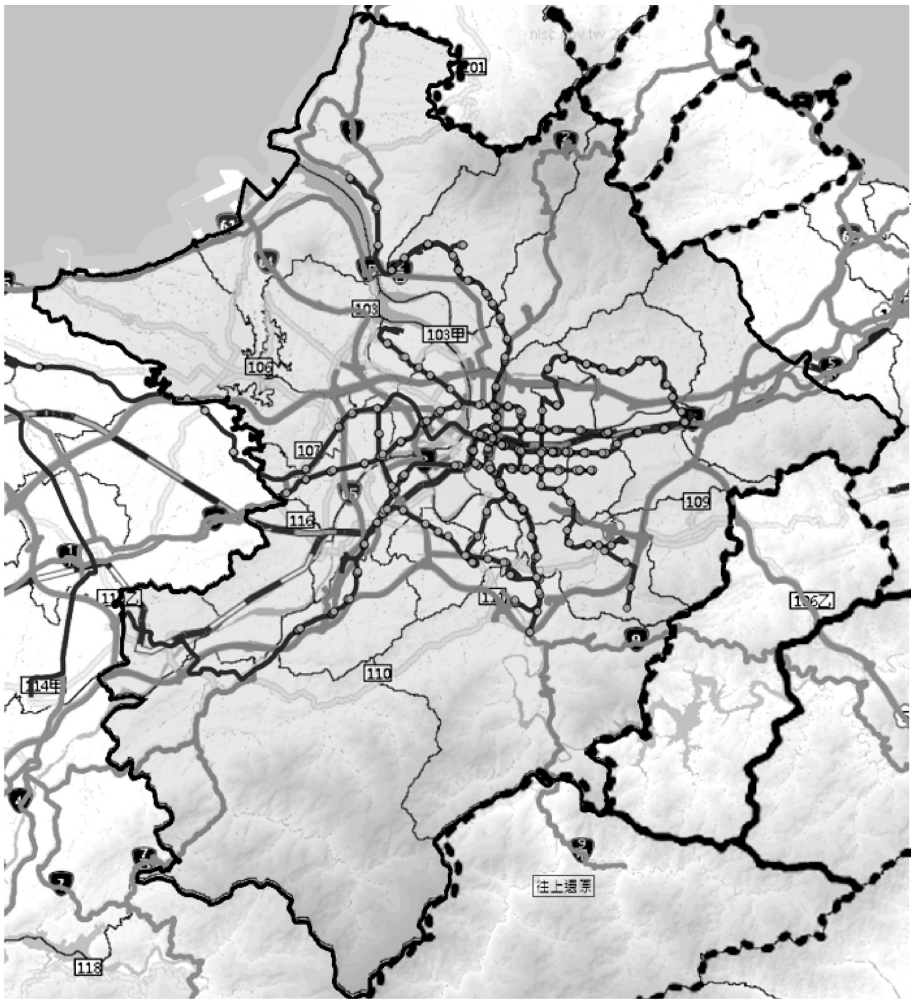

Figure 2 Main Transportation Systems of Taipei Metropolitan Areas

Note: 1. Taipei Basin surrounded by mountains (in green color), and two rivers merging from the south-west and south-east, eventually joining together to the north west. Taipei metropolitan areas (black solid line) are presented in light red color (Taipei City) and light blue color (New Taipei City). The districts in black dot lines are the rural areas in New Taipei City. The transportation infrastructure, including the MRT system (the purple line with yellow dot), highways/freeways (the yellow and orange line), and railway (the black-and-white belt represented Railway and the black-and-yellow belt represented High-Speed Rail (HSR). 2. Source from "Advocate Sharing platform" website: Data.gov.tw, compiled and organized by the author.

Thirdly, district population serves as an indicator of the population agglomeration and neighborhood effect, representing the number of people accustomed to the livability, accessibility, and amenities offered by the districts. Specifically, TC has a population of 2.65 million, while New Taipei City (NTC) boasts 3.96 million residents. Additionally, the regions of TC_HHP and NTC_HHP have the highest population figures. The deviation for both cities indicates the frequency of mobility or the natural birth/death rate. TC (51.63k) exhibits a higher deviation than NTC (47.24k), suggesting a greater vibrancy in mobility within TC.

Table 2 Mean & Trend of Taipei Metropolitan Areas

Region	District	Proportion on migrants from CBD		Distance		Population (10K)		Housing Price (10K)		Housing Supply		Gravity Mass	
Taipei City		0.857%	(0.085%)	0.00	(0.0000)	265.103	(5.163)	56.73	(5.541)	40114	(14629)	-	-
TC High Housing Price (TC_HHP)	Da'an	0.114%	(0.012%)	3.84	(0.0187)	30.943	(0.626)	81.53	(6.452)	2708	(1445)	0.00504954	(0.001467)
	Zongshan	0.092%	(0.011%)	1.01	(0.0262)	22.600	(0.526)	63.75	(8.059)	5289	(2618)	0.01351865	(0.004131)
	Zhongzheng	0.079%	(0.008%)	4.57	(0.0140)	15.954	(0.350)	69.25	(7.397)	2792	(937)	0.00374776	(0.000809)
	Songshan	0.082%	(0.009%)	1.65	(0.0292)	20.667	(0.311)	69.77	(8.727)	1832	(1047)	0.00563268	(0.001959)
	Xinyi	0.070%	(0.010%)	4.31	(0.0417)	22.399	(0.636)	66.63	(5.899)	1988	(1142)	0.00384321	(0.001228)
TC Median Housing Price (TC_MHP)	Neihu	0.081%	(0.010%)	4.86	(0.0474)	28.137	(0.687)	49.07	(5.848)	5539	(2621)	0.00797882	(0.002214)
	Shilin	0.071%	(0.008%)	5.18	(0.0234)	28.551	(0.591)	51.53	(5.152)	2929	(1358)	0.00553655	(0.001558)
	Datong	0.043%	(0.006%)	3.20	(0.0194)	12.714	(0.324)	53.79	(6.710)	2448	(905)	0.00422728	(0.000945)
	Nangang	0.047%	(0.005%)	6.12	(0.0300)	11.894	(0.323)	50.61	(6.327)	2910	(1458)	0.00326524	(0.001000)
TC Low Housing Price (TC_LHP)	Beitou	0.062%	(0.004%)	8.70	(0.0203)	25.324	(0.412)	43.77	(5.853)	4061	(814)	0.00522913	(0.000839)
	Wenshan	0.061%	(0.006%)	7.87	(0.0296)	26.958	(0.531)	42.61	(6.160)	5016	(1169)	0.00638259	(0.001061)
	Wanhua	0.055%	(0.005%)	6.01	(0.0094)	18.964	(0.511)	45.59	(6.773)	2604	(361)	0.00426768	(0.000397)
New Taipei City		1.694%	(0.229%)	13.27	(0.0000)	396.450	(4.724)	28.98	(4.310)	108085	(23656)	0.10646044	(0.019026)
NTC High Housing Price (NTC_HHP)	Banqiao	0.193%	(0.027%)	10.33	(0.0540)	55.481	(0.201)	37.10	(6.404)	11106	(3186)	0.01279393	(0.002780)
	Xindain	0.169%	(0.022%)	13.43	(0.0432)	29.972	(0.281)	32.25	(4.619)	8007	(960)	0.00750969	(0.000935)
	Yonghe	0.099%	(0.017%)	7.12	(0.0165)	22.607	(0.645)	39.62	(5.398)	2272	(597)	0.00429342	(0.000887)
	Zhonghe	0.163%	(0.027%)	9.29	(0.0215)	41.357	(0.262)	35.42	(5.738)	8395	(2967)	0.01033510	(0.002657)
	Sanchong	0.160%	(0.022%)	5.85	(0.0306)	38.782	(0.248)	34.46	(5.179)	7971	(2688)	0.01248524	(0.003112)
NTC Median Housing Price (NTC_MHP)	Xizhi	0.149%	(0.023%)	10.86	(0.0142)	19.678	(0.608)	26.67	(4.269)	4966	(1162)	0.00583325	(0.000915)
	Tucheng	0.072%	(0.012%)	14.36	(0.0157)	23.849	(0.080)	29.09	(5.226)	2714	(1145)	0.00391823	(0.000962)
	Xinzhuang	0.138%	(0.013%)	11.45	(0.0675)	41.245	(0.732)	30.21	(4.642)	10038	(1135)	0.01100608	(0.000861)
	Luzhou	0.072%	(0.010%)	7.98	(0.0311)	20.009	(0.165)	30.42	(4.867)	3566	(1359)	0.00546085	(0.001527)
NTC Low Housing Price (NTC_LHP)	Bali	0.019%	(0.003%)	15.08	(0.0202)	3.738	(0.202)	18.62	(2.874)	1341	(424)	0.00133957	(0.000284)
	Sanxia	0.042%	(0.008%)	22.25	(0.0213)	11.124	(0.537)	21.02	(4.260)	5376	(3034)	0.00357562	(0.001316)
	Wugu	0.029%	(0.004%)	11.98	(0.0975)	8.393	(0.368)	22.84	(4.935)	3433	(1433)	0.00319749	(0.000545)
	Linkou	0.088%	(0.012%)	17.29	(0.0290)	10.085	(1.445)	23.39	(4.315)	11663	(3228)	0.00539782	(0.000963)
	Taishan	0.024%	(0.004%)	13.01	(0.0467)	7.798	(0.088)	25.80	(4.664)	1664	(1119)	0.00194676	(0.000785)
	Tamsui	0.113%	(0.008%)	16.19	(0.2946)	16.257	(1.397)	21.49	(2.307)	17013	(3064)	0.00890951	(0.000973)
	Shenkeng	0.014%	(0.003%)	11.05	(0.0361)	2.357	(0.018)	22.94	(3.762)	581	(378)	0.00071271	(0.000274)
	Shulin	0.061%	(0.015%)	17.11	(0.3362)	18.183	(0.371)	23.81	(4.133)	5008	(4499)	0.00443285	(0.002527)
	Yingge	0.037%	(0.009%)	23.53	(0.0408)	8.754	(0.087)	16.37	(3.758)	1931	(1119)	0.00205655	(0.000609)

Note: 1. () Standard deviation. TC High Housing Price (TC_HHP), TC Median Housing Price (TC_MHP), TC Low Housing Price (TC_LHP), NTC High Housing Price (NTC_HHP), NTC Median Housing Price (NTC_MHP), and NTC Low Housing Price (NTC_LHP). The gravity mass ratios are calculated using Equations (2) and (3), along with the coefficients from Table 4; the value appears "-" in Taipei City because the distance is 0. 2. Compiled and organized by the author.

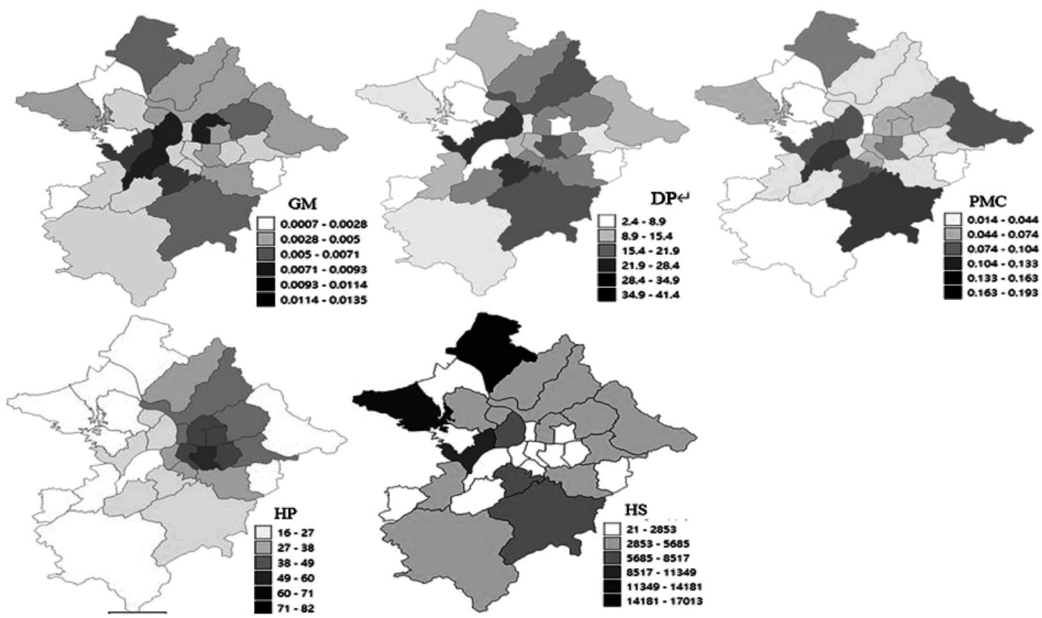

Figure 3 Mean of Taipei Metropolitan Areas in GIS Forms

Note: Compiled and organized by the author.

Fourthly, housing price serves as an indicator of migrant housing affordability. The results indicate that TC (567.3K) has double the housing price compared to NTC (289.8K). Additionally, the standard deviation of TC (55.41K) is larger than NTC (43.10K), suggesting that the financial burden of migrants is more pronounced in TC than in NTC. Furthermore, the housing price has increased from 284.3K (Year 98) to 450.01K (Year 110), indicating a strengthening of the burden over time. Regarding regions, areas closer to the Taipei City exhibit the highest housing prices.

Finally, housing supply represents the housing availability for those migrants when making moving decision, and TC (40K) is much more limited compared with NTC (108K), and the supply has been smaller from 2009 to 2021, which may be explained by the limited amount of land supply. Gravity Mass (attractiveness) represents the combination of determinants of districts for attracting migrants, and it shows that NTC_HHP and TC_MHP are the most attractive areas.

4. Empirical Results

4.1 Empirical Results

Table 3 summarizes our model results. The column “TMA” indicates significance below 1% in the LM test, which rejects the null hypothesis and confirming individual-specific effects among districts. The Hausman test showed the fixed-effects model (FEM) is appropriate, as the p-value is below the 1% significance level. The TMA model has a strong fit with an estimated R^2 (within) of 0.8769 in FEM. Furthermore, we segregated the districts of the TMA into core areas (TC) and fringe

Table 3 Result of Gravity Mass on Mobility

Factors	TMA (Taipei Metropolitan Area)	Core Areas (Taipei City)	Fringe Areas (New Taipei City)
Gravity Mass	0.1295657 (.000)***	0.0639182 (.000)***	0.132495 (.000)***
Constant	-0.0005345 (.000)***	0.0001143 (.052)	-.0006167 (.000)***
R^2 (within)	0.8769	0.6931	0.8895
LM Test	1264.42 (.000)***	779.44 (.000)***	611.72 (.000)***
Hausman Test	30.93 (.000)***	1.59 (0.2077)	30.98 (.000)***
Observations	403	156	247

Note: 1. *** indicates a 1% level of significance. 2. Compiled and organized by the author.

areas (NTC) to discern the difference among two different areas. With the results for TC, it fails the Hausman test; however, it is still significant below 1% in the LM test, which means the model fits the REM with an R^2 (within) of 0.6931. For NTC, it passes both tests with an R^2 (within) of 0.8895 in FEM. Therefore, our proposed model is solid and fits the above three scenarios.

Furthermore, to facilitate the analysis of the determinants, we calculate the logarithm of the model for three groups using random-effects, which is shown in Table 4. The purpose of using random-effects panel data is to emphasize the weighting of each determinant within the gravity model, the results all show fine performance with R^2 over 0.68, and the determinants all show a 1% level of significance, except that the distance impedance has no significance in NTC. By comparing the coefficients, in the TMA, we can see that population is the main driving factor of mobility, with a coefficient as high as 0.7697, and housing price has a negative impact of -0.5205. Distance impedance and housing supply have weaker effects. This means that every 1% increase in population will increase mobility by 0.7697%, and a 1% increase in housing price will decrease mobility by 0.5205%. In TC, population has the highest value (0.4343) and distance has a negative impact of -0.2680. In NTC, population has the highest (0.8368) positive effect, and housing price remains the most negative effect (-0.5821).

4.2 Discussion

Utilizing the modified gravity model, the results obtained at a 1% significance level, with high R^2 value for three groups, provide the solid empirical support for our assumption. It feedbacks to the distance decay on the attractiveness of districts from gravity model perspective (Reilly, 1929; Haynes & Fotheringham, 1990; Zhao et. al., 2021), also explained the intervening opportunities affect their moving decision (Barbosa et al., 2018). This suggests that each district possesses its own mass (attractiveness) for residential mobility, which is determined by the aforementioned three main factors and distance impedance. This directly answers our first core research question: “Where to move?” that migrants exhibit a tendency to relocate to destinations with larger mass relative to their original residential area, indicating that smaller mass districts exert less attraction. Notably, districts

Table 4 Result of Gravity Mass in Logarithm in REM

Description	Variable	TMA (Taipei Metropolitan Area)	Core Areas (Taipei City)	Fringe Areas (New Taipei City)
Distance	Log D	-0.2338 (.000)***	-0.2680 (.000)***	-0.3940 (.022)
Population	Log DP	0.7697 (.000)***	0.4343 (.000)***	0.8368 (.000)***
Housing Price	Log HP	-0.5205 (.000)***	-0.2104 (.000)***	-0.5821 (.000)***
Housing Supply	Log HS	0.1399 (.000)***	0.1656 (.000)***	0.1366 (.000)***
Constant		-6.6765 (.000)***	-5.5167 (.000)***	-6.7443 (.000)***
R^2 (within)		0.7029	0.679	0.736

Note: 1. *** indicates a 1% level of significance. 2. Compiled and organized by the author.

such as NTC high housing price regions which demonstrate gravitational mass values exceeding 0.01, collectively accounting for an average of 0.154% of Taipei citizens in each district from table 2. In-depth with these districts, they have the sufficient housing supply and large population (neighborhood) effect with the adequate housing price and distance impedance.

The panel-data analysis delves deeper into assessing the influence of district-specific and time-series effects on mobility patterns using the gravity model. Determining whether a Fixed Effects or Random Effects model is appropriate involves conducting LM and Hausman tests, with the results outlined in Table 3. Both Taipei metropolitan areas (TMA) and fringe areas (NTC) align with the FE model. This suggests a district-specific time-invariance effect, indicating that each district possesses unique attractiveness. These may encompass public facilities, population distribution, among other factors, contributing to the district-specific effect. Conversely, TC only conform to the RE model. This implies that the RE model, which treats district-specific time-invariance variables as random error or constant, is more suitable. Consequently, migrants exert lesser influence on districts within TC. Furthermore, these district-specific effects wield significant sway over mobility patterns, particularly evident in districts within regions characterized by high housing prices in “NTC high housing price” areas.

In order to facilitate our IUMGM model, we take Eq. (2) into logarithmic form using RE, and Table 4 presents the results. It confirms that the model achieves a fine performance (R^2 (within) = 0.7029). All variables are significant at the 1% level, showing that these indicators well explain the variation in our IUMGM. These findings directly address our second core research question, “How to choose?”, by demonstrating that migrants prioritize population agglomeration and housing affordability over distance impedance. The results highlight that the decision-making process involves a trade-off between economic constraints and spatial accessibility, further validating the theoretical foundations of our modified gravity model.

By comparing the coefficients, we can see that the Population has the most positive factor that driving on residential mobility with a coefficient of 0.7697, which indicating 1% increase in the population will cause the mobility flow to increase by about 0.7697%. It feedbacks to the population agglomeration caused by various factors such as urban economics, environmental factors, resources, and transportation which represented the residential liveability (Lemoine-Rodríguez et. al., 2020; Turok et. al., 2021). Meanwhile, Residential mobility behaviors influenced by their knowledge of a local area which bounded by distances within in specific sections of the city (Lalli, 1992; Hay, 1998; Devine-Wright & Lyons, 1997; Jorgensen & Stedman, 2001; Gustafson, 2014; Oishi & Schimmack, 2010) therefore, our model again prove the primary purpose of improving livability through relocation along with the Reilly's concept.

Followed by housing price, which exhibits a coefficient of -0.5205, indicating that a 1% increase in housing price corresponds to a 0.5205% decrease in residential mobility. Research demonstrates that the structure of housing markets significantly influences housing prices, presenting affordability challenges for many households and impacting their relocation decisions (Lee et al., 2000; Baker, 2016). Next in line is distance impedance, with a coefficient of -0.2338, emphasizing the fundamental role of distance in mobility, aligning with the concept of gravity. This parameter is integrated into our IUMGM model (Zipf, 1946; Haynes & Fotheringham, 1990; Zhao et. al., 2021; Barbosa et al., 2018). Lastly, housing supply exhibits the least influence, with a coefficient of 0.1399, suggesting that residential mobility is primarily voluntary and driven by market forces. Households adjust their housing consumption based on factors such as space, location, amenity, or quality (Strassmann, 1991; Dieleman et al., 2000; Van der Vlist et al., 2002; Van Ommeren & Van Leuvensteijn, 2005). A sufficient housing supply could potentially increase mobility (Peng et al., 2009).

This dynamic adjustment of housing consumption to market conditions underscores the significance of housing market factors in intra-urban relocations, as emphasized by various researchers (Strassmann, 1991; Dieleman, 2001; Chen & Peng, 2024). They suggest that, in terms of priority, considerations for mobility are ranked as follows: the population holds the highest importance, followed by housing affordability (housing price). Subsequently, individuals may explore areas further afield before considering the availability of housing when selecting a destination,

We further divided the overall data into core areas (TC) and fringe areas (NTC), as shown in Tables 4. Both models exhibit significance at the 1% level, yet NTC demonstrate a higher R-squared value (0.8895) compared to TC (0.6931). Consequently, the model is deemed to be more accurate when applied to the new suburban areas. Table 4 depicts the results when applying the model to logarithm, aimed at understanding the weighting of determinants influencing the choice of core and, as well as how these districts attract migrants. The findings reveal that the population carries the most weight in NTC (0.8368), demonstrating 1% significance, whereas in TC, it exhibits 1% significance (0.4343). This suggests that migrants consider the population factor more strongly in NTC, where it may reflect perceptions of livability and accessibility.

Furthermore, housing price displays significance at the 1% level in both areas, yet its impact is more pronounced in NTC (-0.5821) compared to TC (-0.2104), indicating that housing affordability is a more significant consideration for individuals relocating to NTC. In contrast, housing supply holds less weight in migrants' considerations, with similar coefficients observed in both TC (0.1656) and NTC (0.1366). Distance, however, demonstrates no significance in either area. In summary, the determinants influencing migrants' decision-making in new areas indicate that the population and housing price play crucial roles, particularly in attracting individuals from their original areas to fringe areas. Housing supply holds less significance in the decision-making process, and distance appears to be less critical overall.

5. Conclusion

Research on the factors influencing residential mobility provides insights into urban growth, transformation, and restructuring (Dieleman, 2001). While previous researches have explored residential relocations and the reasons behind moving, a significant gap remains in analyzing mobility patterns within the context of housing market dynamics and competition (Ermisch & Washbrook, 2012). Additionally, research on urban structural changes often overlooks spatial interconnections between districts. To address this gap, our model simulates urban expansion using the gravity model, incorporating residential mobility to emerging suburban areas and integrating intervening opportunities.

Regarding regional differences, our findings align with established theories: larger population sizes at both origin and destination promote migration, while greater distances reduce migration, and the results support the efficacy of our model. (Zipf, 1946; Haynes & Fotheringham, 1990; Zhao et. al., 2021). The indicators chosen for our study are grounded in previous research, further strengthening the model's theoretical and practical basis.

Consequently, our model demonstrates broad applicability with minor modifications, requiring adjustments to determinants and recalibration to accommodate regional characteristics. This flexibility ensures its effectiveness in capturing population mobility dynamics across diverse contexts. By integrating both residents' motivations and district attractiveness, the model identifies core district competencies and competitive interactions. Moreover, migrants from different socioeconomic groups experience distinct influencing factors and varying sensitivities to distance impedance. To account for these differences, the coefficient γ in Equation (5) can be adjusted, with higher values assigned to groups more affected by distance and lower values to those less sensitive, ensuring a nuanced representation of mobility patterns.

Policy scenario experiments can assess the impact of urban policies on population distribution by adjusting input parameters. For instance, modifying housing supply layouts through land replotting within the Intra-Urban Mobility Gravity Model (IUMGM) allows for simulating mobility patterns and analyzing distribution shifts. Similarly, new public facilities or transportation improvements can influence population agglomeration, alter housing prices, and reshape migration trends. This approach provides a structured framework for evaluating policy interventions and their effects on urban dynamics.

Moreover, while our study confirms the influence of population, housing prices, supply, and distance on migration patterns, our findings confirm the influence of population, housing prices, supply, and distance on migration patterns within TMA. However, additional factors such as urban renewal, an aging society, and the rise of remote work may also play a role in shaping residential market dynamics. These elements, while not included in the current empirical model due to data limitations, warrant further investigation in future research. For instance, as remote work gains popularity, some residents are relocating to peripheral areas with better greater livability, altering traditional migration patterns. Additionally, rapid housing price growth has intensified affordability concerns, distinguishing Taipei's migration dynamics from those in Western cities. Future research could further examine these factors to refine housing policies, enhance infrastructure, and support urban planning strategies that accommodate remote work. These insights not only validate existing migration theories but also highlight region-specific dynamics, offering valuable implications for policy-making.

This paper presents the Intra-Urban Mobility Gravity Model (IUMGM) to simulate intra-urban population mobility, incorporating district mass factors, directional mobility, and distance impedance. Key determinants include population, housing prices, housing supply, and distance impedance, ensuring a theoretically grounded and adaptable framework. As a rigorous application of the gravity model, the IUMGM demonstrates strong predictive capability and broad applicability, requiring only minor adjustments for different contexts. By advancing gravity theory in mobility research, this study offers valuable insights into urban migration dynamics.

Note

Note. 1 The study period 2009 to 2021is limited by Taiwan's migration statistics, which classify population flows into three categories: movements between the six municipalities and Taiwan Province, migrations within the same county or city, and address changes within districts. Non-municipality counties are grouped under "Taiwan Province," making individual migration figures unavailable. Since New Taipei City was upgraded from Taipei County in 2010, district-level migration data is only traceable back to 2009.

Note. 2 The sources are from the websites of Taipei City Government, New Taipei City Government, and the "Industry, Commerce and Service Census" under National Statistic, R.O.C. (Taiwan) https://www.stat.gov.tw/News.aspx?n=2738&sms=11057

Note. 3 The PMT ratio is calculated as the number of migrants in Taipei City divided by its population. The available district-level migration data (as discussed in Section 3.2) include only three categories: (1) intra-district migration, (2) inter-district migration within the same city, and (3) migration between Taipei City and New Taipei City, covering the period from 2009 onward. Given these limitations, this study treats Taipei City as a single administrative unit to assess its influence on migration dynamics across districts in both cities. Accordingly, category (2) inter-district migration within the same city is used for districts within Taipei City, while category (3) migration from Taipei City to New Taipei City is applied for districts in New Taipei City.

Note. 4 Kumler, M. P., & Goodchild, M. F. (1992). The population center of Canada-just north of Toronto. Geographical Snapshots of North America, 275-279.

Note. 5 The Vital Registration of Household Statistics offers detailed information on population and migration trends from 1998 to the present, while the Ministry of the Interior's Real Estate Information Platform provides comprehensive data on housing prices and housing supply from 2007 onwards. In reality, the population data obtained from household registration may differ from the real residential population. As for the "Report on the Internal Migration Survey" for 2012, it has been calculated that the population of household registration reaches up to 90% of the real residential population, based on which the variance is acceptable and the results for our paper remain the same.

Note. 6 The classification of TMA districts into six distinct regions is based on the Cathay Real Estate Price Index. Source from: https://www.cathay-red.com.tw/tw/About/House.

References

Arribas-Bel, D. & F. Sanz-Gracia

2014 “The Validity of the Monocentric City Model in a Polycentric Age: US Metropolitan Areas in 1990, 2000 and 2010,” *Urban Geography*. 35(7): 980-997.

Baker, D.

2016 “The Upward Redistribution of Income: are Rents the Story?,” *Review of Radical Political Economics*. 48(4): 529-543.

Barbosa, H., M. Barthelemy, G. Ghoshal, C. R. James, M. Lenormand, T. Louail, R. Menezes, J. Ramasco, F. Simini & M. Tomasini

2018 “Human Mobility: Models and Applications,” *Physics Reports*. 734: 1-74.

Bardhan, A., R. H. Edelstein & C. A. Kroll (Eds.)

2011 *Global Housing Markets: Crises, Policies, and Institutions*. New York: John Wiley & Sons.

Bettencourt, L. M.

2021 *Introduction to Urban Science: Evidence and Theory of Cities as Complex Systems*. Cambridge, MA: The MIT Press.

Breusch, T. S. & A. R. Pagan

1980 “The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics,” *The Review of Economic Studies*. 47(1): 239-253.

Chang T. C.

2013 “Gender selection in destination choices of labor migration,’’ *Journal of Housing Studies*. 22(1): 1-24. (in Chinese with English abstract)

Chen, P. H. & C. W. Peng

2024 “Determinants of intra-district residential mobility: A case study of Taipei Metropolitan Areas,” *International Real Estate Review*. 27(3): 329-359.

Clark, W. A. V.

2013 “Life Course Events & Residential Change: Unpacking Age Effects on the Probability of Moving,” *Journal of Population Research*. 30(4): 319-334.

2020 *Human Migration*. Morgantown. WV: WVU Research Repository.

de Dios, O. J. & L. Willumsen

2011 *Modeling Transport*. New York: John Wiley and Sons Ltd.

Deimantas, V. J.

2023 “Life Course Decisions in Central and Eastern Europe: A Gendered Connection between Family Formation and Moving Intentions?,” *JFR-Journal of Family Research*. 35: 232-250.

Devine-Wright, P. & E. Lyons

1997 “Remembering pasts and representing places: The construction of national identities in Ireland,” *Journal of Environmental Psychology*. 17(1): 33-45.

Dieleman, F. M.

2001 "Modelling Residential Mobility: A Review of Recent Trends in Research," *Journal of Housing & the Built Environment*. 16: 249-265.

Dieleman, F. M., W. A. Clark & M. C. Deurloo

2000 "The Geography of Residential Turnover in Twenty-seven Large US Metropolitan Housing Markets, 1985-95," *Urban Studies*. 37(2): 223-245.

Ermisch, J., & E. Washbrook

2012 "Residential Mobility: Wealth, Demographic & Housing Market Effects," *Scottish Journal of Political Economy*. 59(5): 483-499.

Fang, C. & D. Yu

2017 "Urban Agglomeration: An Evolving Concept of an Emerging Phenomenon," *Landscape and Urban Planning*. 162: 126-136.

Garemo, N., J. Mischke, S. Ramt, S. Sankhe & J. Woetzel

2014 *A Blueprint for Addressing the Global Affordable Housing Challenge*. New York: McKinsey Global Institute.

Gustafson, P.

2014 "Place Attachment in an Age of Mobility," *Place attachment. Advances in Theory, Methods and Applications*. London: Routledge.

Guo, J., T. Feng & H. J. Timmermans

2020 "Co-dependent Workplace, Residence and Commuting Mode Choice: Results of a Multi-dimensional Mixed Logit Model with Panel Effects," *Cities*. 96: 102448.

Hausman, J. A.

1978 "Specification Tests in Econometrics," *Econometrica*. 46(6): 1251-1271.

Hay, R.

1998 "Sense of Place in Developmental Context," *Journal of Environmental Psychology*. 18(1): 5-29.

Haynes, K. E. & A. S. Fotheringham

1990 "The Impact of Space on the Application of Discrete Choice Models," *Review of Regional Studies*. 20(2): 39-49.

2020 *Gravity and Spatial Interaction Models Morgantown*. WV: Regional Research Institute, West Virginia University.

He, Y., G. Zhou, C. Tang, S. Fan & X. Guo

2019 "The Spatial Organization Pattern of Urban-rural Integration in Urban Agglomerations in China: An Agglomeration-diffusion Analysis of the Population and Firms," *Habitat International*. 87: 54-65.

Hua, C. C.

2001 "Ownership rate, vacancy, and the adjustment of housing market," *Journal of Housing Studies*. 10(2): 127-137 (in Chinese with English abstract).

Jorgensen, B. S. & R. C. Stedman.

2020 "Sense of place as an attitude: lakeshore owners attitudes toward their properties," *Journal of Environmental Psychology*. 21(3): 233-248.

Lalli, M.

1992 "Urban-related Identity: Theory, Measurement, & Empirical Findings," *Journal of Environmental Psychology*. 12(4): 285-303.

Lee, B. H. Y. & P. Waddell

2010 "Residential Mobility and Location Choice: A Nested Logit Model with Sampling of Alternatives," *Transportation*. 37(4): 587-601.

Lee, S. W., D. Myers & H. S. Park

2000 "An Econometric Model of Homeownership: Single-family and Multifamily Housing Option," *Environment and Planning A*. 32(11): 1959-1976.

Levine, J., J. Grengs & L. A. Merlin

2019 *From mobility to Accessibility: Transforming Urban Transportation and Land-use Planning Ithaca*. NY: Cornell University Press.

Li, T., S. J. Shiran & J. Dodson

2021 "Metropolitan Migration and Spatial Housing Markets: A Geographical Study in Melbourne," *Applied Geography*. 129: 102414.

Lin, Y. J.

2021 "Differences & myths about house price-to-income ratios in Taiwan's seven largest cities: an analysis of buyers' house ownership & subjective factors," *Journal of Housing Studies*. 30(1): 27-47 (in Chinese with English abstract).

Lemoine-Rodríguez, R., L. Inostroza & H. Zepp

2020 "The Global Homogenization of Urban Form. An Assessment of 194 Cities across Time," *Landscape and Urban Planning*. 204: 103949.

Liu, W.

2015 "The Influence of Housing Characteristics on Rural Migrants' Living Condition in Beijing Fengtai District," *HBRC Journal*. 11(2): 252-263.

Molloy, R., C. L. Smith & A. Wozniak

2017 "Job Changing and the Decline in Long-distance Migration in the United States," *Demography*. 54(2): 631-653.

Niu, F.

2022 "A Push-pull Model for Inter-city Migration Simulation," *Cities*. 131: 104005.

Oishi, S. & U. Schimmack

2010 "Residential Mobility, Well-being, and Mortality," *Journal of Personality and Social Psychology*. 98(6): 980-994.

Pacione, M.

1990 "Urban Liveability: A Review," *Urban Geography*. 11(1): 1-30.

Peng, C. W., W. C. Wu & S. Y. Kung
2009 "An analysis of determinants of residential migration," *Journal of Population Studies*. 39: 85-118. (in Chinese with English abstract)

Peng, C. W. & I. C. Tsai
2019 "The long- and short-run influences of housing prices on migration," *Cities*. *93*: 253-262.

Reilly, W. J.
1929 *Methods for the Study of Retail Relationships*. Austin: University of Texas, Bureau of Business Research.

Ruth, M. & R. S. Franklin
2014 "Livability for All? Conceptual Limits and Practical Implications," *Applied Geography*. 49: 18-23.

Scott, P.
2017 *Geography and retailing*. London: Routledge.

Simini, F., M. C. González, A. Maritan & A. Barabasi
2012 "A Universal Model for Mobility and Migration Patterns," *Nature*. 484: 96-100.

Simini, F., A. Maritan & Z. Neda
2013 "Human Mobility in a Continuum Approach," *PLoS One*. 8(3): e60069.

Skakkebæk, N. E., R. Lindahl-Jacobsen, H. Levine, A. M. Andersson, N. Jørgensen, K. M. Main, Ø. Lidegaard, L. Priskorn, S. A. Holmboe, E. V. Bräuner, K. Almstrup, L. R. Franca, A. Znaor, A. Kortenkamp, R. J. Hart & A. Juul
2022 "Environmental Factors in Declining Human Fertility," *Nature Reviews Endocrinology*. 18(3): 139-157.

Strassmann, W. P.
1991 "Housing Market Interventions and Mobility: An International Comparison," *Urban Studies*. 28(5): 759-771.

Stouffer, S. A.
1940 "Intervening opportunities: A theory relating mobility and distance," *American Sociological Review*. 5(6): 845-867.

Turok, I., L. Seeliger & J. Visagie
2021 "Restoring the Core? Central City Decline and Transformation in the South," *Progress in Planning*. 144: 100434.

Van der Vlist, A. J., C. Gorter & P. Nijkamp
2002 "Residential Mobility and Local Housing-market Differences," *Environment and Planning A*. 34(7): 1147-1164.

Van Ommeren, J. & M. Van Leuvensteijn
2005 "New Evidence of the Effect of Transaction Costs on Residential Mobility," *Journal of Regional Science*. 45(4): 681-702.

Wang, C. & Z. H. Wang

2017 "Projecting Population Growth as a Dynamic Measure of Regional Urban Warming," *Sustainable Cities and Society*. 32: 357-365.

Wilson, A. G.

1971 "A Family of Spatial Interaction Models, and Associated Development," *Environment and Planning A*. 3(1): 1-32.

Wu, J., A. Bernard & E. Gruber

2024 "Lifetime Internal Migration Trajectories and Social Networks: Do Repeat Migrants Fare Worst?," *Social Networks*. 79: 133-152.

You, Z., H. Yang & M. Fu

2018 "Settlement Intention Characteristics and Determinants in Floating Populations in Chinese Border Cities," *Sustainable Cities and Society*. 39: 476-486.

Zabel, J. E.

2012 "Migration, Housing Market, & Labor Market Responses to Employment Shocks," *Journal of Urban Economics*. 72(2-3): 267-284.

Zhao, Y., G. Zhang & H. Zhao

2021 "Spatial Network Structures of Urban Agglomeration Based on the Improved Gravity Model: A Case Study in China's Two Urban Agglomerations," *Complexity*. 2021(1): 6651444.

Zipf, G. K.

1946 "The P1 P2/D Hypothesis: on the Intercity Movement of Persons," *American Sociological Review*. 11(6): 677-686.