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Analysing Population Displacement and Financial Precarity Induced by Gentrification based on Social Mix Perspective

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1 ABSTRACT

This study investigates the spatial dynamics of gentrification and upward filtering in Taipei City, a metropolis characterized by Taiwan's highest population density and acute housing affordability challenges. Examining the interplay between financial precarity and population displacement, this research analyzes distinct patterns of neighborhood change within this dense urban context. Comparative analysis reveals that areas experiencing upward filtering, marked by increased real estate transaction volumes, exhibit a stronger correlation between market activity and rent prices, highlighting the direct impact of real estate dynamics on affordability. Conversely, the observed decline in high-income and highly educated residents in other areas suggests potential displacement pressures. Despite these shifts, the absence of strong spatial autocorrelation between real estate transactions and rent prices indicates the significant influence of localized factors, such as zoning policies, on rent price dynamics. Bivariate spatial autocorrelation analysis further underscores the interconnectedness of demographic changes, particularly the clustering of high-income and highly educated populations in upward-filtering areas. These findings contribute to a nuanced understanding of gentrification and upward filtering within Taipei's unique urban landscape, providing insights for policies aimed at mitigating financial precarity and fostering equitable urban development.

Keywords: Gentrification, Financial Precarity, Population Displacement, Bivariate Spatial Autocorrelation, Planning

2 INTRODUCTION

Gentrification, originally conceptualized in 1964 by British sociologist Ruth Glass, describes the process of social mobility within urban centers. Glass observed that in London, the middle class progressively encroached upon working-class neighborhoods. As rental contracts expired, deteriorated housing units were reclaimed, renovated, or even reconstructed, facilitating the redevelopment of declining urban areas. This transformation, however, led to the displacement of the proletariat, triggering significant socio-economic consequences (Glass, 1964). Gentrification is no longer confined to inner-city areas but has expanded to peripheral urban zones (Williams, 1984) and even economically abandoned spaces that were previously developed but have since been left vacant (Schaffer & Smith, 19 86). Urban shrinkage has been identified as a driver that creates new potential for gentrification (Oswalt, 2006). As a dynamic urban process, gentrification reshapes the socio-economic composition of neighborhoods, leading to class replacement and the emergence of new industries (Hamnett, 2003; Kennedy & Leonard, 2001). In the early 2000s, policy-oriented research began framing gentrification as a positive urban development strategy – one that could foster the revitalization of disadvantaged areas and promote social integration. Through infrastructure improvements, better housing conditions, and job creation, gentrification has been seen as a means to drive the redevelopment of marginalized urban areas and enhance social cohesion (Arthurson, 2010; Lees, 2008).

However, numerous studies have found that gentrification often leads to the displacement of economically vulnerable households and contributes to psychosocial stress and educational resource disparities in gentrified areas (Martin & Beck, 2018; Davidson, 2010; Wyly et al., 2010). While gentrification, as an urban renewal strategy, can promote community integration and reduce social exclusion in certain contexts, it also presents significant negative consequences in practice. For instance, the East End Regeneration Program in London aimed to revitalize impoverished communities in East London by improving infrastructure and attracting new industries to stimulate local economic development. In the short term, the program successfully enhanced housing quality and public amenities, attracting young professionals to the area (Butler & Robson, 2003). However, it simultaneously exacerbated housing affordability issues for long-term residents, forcing some low-income families to relocate (Atkinson, 2004).

The factors driving displacement can be broadly categorized into material and conceptual aspects. Material factors include direct influences such as housing prices and living conditions, while conceptual factors are primarily based on residents' perceptions and lived experiences (Phillips et al., 2021). Displacement itself can be classified into three types: direct or physical, indirect or economic, and exclusionary factors. Forced displacement refers to situations where legal policies or external forces compel residents to relocate, while “responses and impacts” describe the broader consequences of environmental change. Among these factors, indirect or economic displacement is closely linked to gentrification. For example, transportation infrastructure projects and public investments often lead to rising property values and rental costs, making housing unaffordable for existing residents and triggering migration (Zuk et al., 2017).

Original residents and tenants may be forced to relocate due to economic pressures, environmental changes, or personal development factors. This migration pattern is often characterized by “downward filtering”, where displaced populations move to areas with lower living costs and standards. Conversely, “upward filtering” refers to higher-income individuals moving into city centers or well-developed neighborhoods, driving up housing prices and gradually replacing lower-income residents with an upper-middle-class demographic (Covington & Taylor, 1989).

On the other hand, the relationship between gentrification and financial precarity has increasingly become a crucial topic in urban studies (Smith, 1987; Lees et al., 2008; Zuk et al., 2018). Financial precarity is generally understood as a multidimensional phenomenon, encompassing financial stress and vulnerabilities at the individual, household, and community levels (Standing, 2012; Kalleberg, 2018). During the gentrification process, the influx of high-income groups reshapes the local economic structure, leading to rising housing costs and increasing overall living expenses, which further intensifies financial pressures on original residents (Smith, 1996; Zuk et al., 2017). This economic pressure often manifests in rising housing prices and rents, increasing costs for basic services, and overall higher daily living expenses. Previous studies indicate that financial precarity typically reduces individuals' and households' financial resources, limiting their ability to cope with economic fluctuations or unexpected crises (Desmond, 2016; Morduch & Schneider, 2017). In gentrified neighborhoods, low-income families frequently experience financial stress, including declining savings capacity, rising debt burdens, and even forced displacement from their communities (Newman & Wyly, 2006; Holme, 2002). Economic precarity in gentrification also extends to changes in the local labor market. The influx of high-income residents often drives a transformation of the regional economic structure, fostering the growth of high-end service industries while simultaneously displacing traditional service sectors and local workers, leading to labor market polarization (Hamnett, 2003). In the short term, this transition may contribute to economic growth, but for original residents, it often results in a mismatch between skill demand and income structures, exacerbating their economic vulnerability (Braveman et al., 2011).

Moreover, financial precarity induced by gentrification is often intertwined with issues of spatial inequality. While urban development policies aim to promote urban renewal, they often lead to unequal resource distribution, further widening social and economic disparities within urban spaces (Adger, 2000; Smith, 1996). For instance, the upgrading of public infrastructure and the influx of high-value commercial investments attract additional capital to gentrified areas, pushing housing costs even higher. At the same time, public service resources may be reallocated to cater to high-income groups, potentially reducing access to essential services for lower-income residents (Morduch & Schneider, 2017). This phenomenon not only weakens marginalized groups' ability to access public resources but may also reinforce financial precarity within gentrified neighborhoods (Holme, 2002). In the gentrification process, balancing economic development and social equity while mitigating the impact of financial precarity on vulnerable populations remains a key challenge for urban development policies (Standing, 2012; Newman & Wyly, 2006).

This study aims to investigate the spatial distribution characteristics and correlation between financial precarity factors and population displacement factors in the context of gentrification by examining the spatial composition characteristics of gentrification.

3 RESEARCH DESIGN

3.1 Materials

3.1.1 Study area

This study focuses on the metropolitan area of Taipei City (Fig. 1) as the research site, excluding areas such as mountains, rivers, parks (e.g., Daan Forest Park, Youth Park), and Songshan Airport. Taipei City, characterized by Taiwan's highest population density and high housing prices, is a suitable location for investigating gentrification.

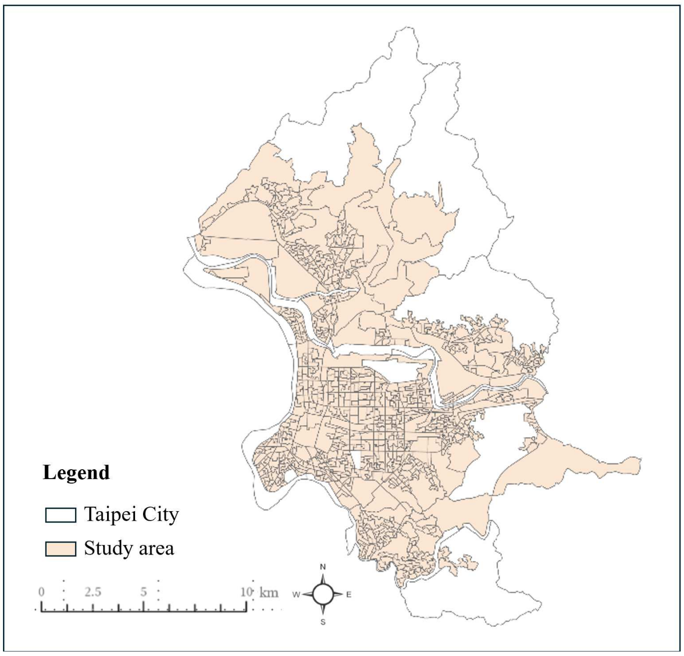

Fig. 1: Study area

3.1.2 Indicators of gentrification and financial precarity

To ensure temporal and spatial consistency in identifying gentrified displacement areas, it is important to have precise indicator years. Therefore, this study sets the data collection period from 2013 to 2019, and all data sources and years are shown in Table 1.

Subject	Indicator		Data Source (Year)
Demographic mobility	M1	Total number of immigrants	Social Economic Data Service Platform (2023)
	M2	Total number of emigrants	
	M3	Change rate of high-income population	Ministry of Finance, Executive Yuan (2022)
	M4	Change rate of low-income population	
	M5	Change rate of highly educated population	Social Economic Data Service Platform (2023)
Demographic Structure	P1	Percentage of high-income population	Ministry of Finance, Executive Yuan (2022)
	P2	Percentage of low-income population	
	P3	Percentage of highly educated population	Social Economic Data Service Platform (2023)
	P4	Percentage of young and middle-aged population	Social Economic Data Service Platform (2023)
	P5	Percentage of disabled population	Social Economic Data Service Platform (2023)
Real Estate characteristic	R1	Real estate transaction volume	Real Estate Transaction Cases – Actual Information Data Supply System, Ministry of the Interior, Executive Yuan (2023)
	R2	Housing rent price	
	R3	Change rate of housing purchases	
	R4	Change rate of housing rent	

Table 1: Indicators of gentrification

This study focuses on the phenomenon of gentrification and, specifically, examines variables related to “financial precarity” within this context. From the broader set of gentrification indicators, a selection of key variables has been identified and isolated for further analysis due to their direct relevance to financial precarity. These selected indicators, along with their explanations and supporting academic literature, are detailed below (Table 2). This focused approach allows for a deeper investigation into the complex relationship between gentrification and the precarious economic conditions that can arise within changing neighborhoods.

Indicator	Explanation	References
M3 Change Rate of High-Income Population	Influx of high-income residents can inflate housing costs, displacing existing residents and creating financial strain. Outflow can signal declining opportunities.	Florida, R. (2002); Moretti, E. (2012)
M5 Change Rate of Highly Educated Population	Shifts in the educated population can intensify job competition, creating or worsening financial precarity for less-educated residents.	Lucas, R. E. (1988); Goldin, C. D., & Katz, L. F. (2018); Autor, D. H. (2014)
R1 Real Estate Transaction Volume	High transaction volume can signal speculation and rapid neighborhood change, leading to displacement and increased financial precarity.	Case, K. E., & Shiller, R. J. (1989); Glaeser, E. L., & Nathanson, N. (2017)
R2 Housing Rent Price	Rapid rent increases directly strain budgets and can lead to displacement, a key mechanism of gentrification-driven financial precarity.	Glaeser, E. L., & Gyourko, J. (2008); Mayer, C., & Somerville, C. T. (2000); Desmond, M. (2016)

3.2 Methods

3.2.1 Principal components analysis

Principal Component Analysis (PCA), a widely employed multivariate statistical technique, serves as a dimensionality reduction method. Initially proposed by Pearson (1901) and further developed by Hotelling (1933), PCA is primarily utilized to determine the weights of individual variables in order to construct composite indicators. The primary objective of PCA is to identify a set of linear combinations that retain the information inherent in the original variables (representativeness), ensure that the composite indicators (principal components) are uncorrelated (independence), and achieve a parsimonious representation of the original variables by a reduced number of composite indicators (parsimony).

$$\begin{cases} U_1 = l_{11}x_1 + l_{12}x_2 + \cdots + l_{1p}x_p \\ U_2 = l_{21}x_1 + l_{22}x_2 + \cdots + l_{2p}x_p \\ \quad\cdots \\ U_m = l_{m1}x_1 + l_{m2}x_2 + \cdots + l_{mp}x_p \end{cases}$$

where m refers to the spatial units, p refers to the number of attributes, x_p refers to the original attributes, l_{mp} is the factor loading, and U_m refers to the principal components. U_1, U_2, …, U_m (with $m \leq p$) are linear combinations of x_p.

Gentrification is composed of a variety of indicators, and the appropriate indicator forms vary depending on the country, city, historical culture, and other factors. Therefore, it is crucial to determine how to calculate and combine these indicators to reflect the texture of gentrification in Taipei. In this study, the standardized indicator values of each indicator will be integrated and weighted using Principal Component Analysis (PCA) to construct "Principal Component Groups" (hereinafter referred to as composite indicators) under various measurement standards. This approach allows for the analysis of gentrification patterns under different composite indicators. Finally, the composite indicator scores will be calculated and mapped, followed by spatial analysis to identify the secondary release areas with migratory characteristics of gentrification in Taipei City.

3.2.2 Pearson's Correlation Coefficient

Pearson's Correlation Coefficient, developed by Karl Pearson, is a statistical measure that quantifies the degree of linear association between two continuous variables. It is widely used in various fields to explore the relationships between variables.

$$r(x,y) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

The coefficient, denoted as r, ranges from -1 to +1. +1 indicates a perfect positive correlation, meaning that the two variables increase or decrease together in a perfectly linear fashion. 0 indicates no linear correlation, suggesting that the variables do not have a linear relationship.

In this study, Pearson's Correlation Coefficient will be employed to investigate the linear relationships between variables related to gentrification and financial precarity.

3.2.3 Local indicators of spatial association (LISA) and Bivariate Spatial Autocorrelation

The local index of spatial correlation can be used to identify the different spatial correlation and aggregation patterns that may exist in different spatial locations, and then find out the spatial heterogeneity between data (Anselin 2010). Also known as Local Moran's I Index. It mainly uses the spatial pattern comparison with neighboring areas to find out areas with similar or different patterns to define cluster areas and expresses them with local correlation distribution maps. Statistics calculation method:

$$I_i = \frac{n(x_i-\bar{x})\sum_j W_{ij}(x_j-\bar{x})}{\sum_i (x_i-\bar{x})^2} = \frac{nz_i\sum_j W_{ij}z_j}{z^T z} = z_i^T \sum_j W_{ij} z_j^T$$

Among them z_i^T and z_j^T Tare the average standardized observation values of the observation values. W_{ij} is the spatial adjacent weight matrix of space unit *i* and *j* area *(j=1,2,3,...,n)* within the research scope, Wij=1 means *i* and *j* are adjacent, and W_{ij}=0 means *i* and *j* are not adjacent.

In the local spatial autocorrelation analysis, when the observation value of itself and the neighboring area are both high (higher than the average), it can be represented by High-High (HH); when the observation value of itself and the neighboring area are both low, it can be Low -Low (LL) means; in addition when the own observation value is high, the surrounding low is expressed as High-Low, and when the own observation value is low, the surrounding high is expressed as Low-High.

Based on spatial correlation analysis, Anselin et al. (2010) developed a bivariate local indicator of spatial association (LISA) to measure local spatial correlation and identify the type of spatial correlation between the two variables. This method is a local bivariate Moran's I statistic and is defined as:

$$I_{kl}^i = Z_k^i \sum\nolimits_{j=1}^{n} W_{ij} Z_j^i$$

where W_{ij} represents the spatially weighted matrix,

$$Z_j^i = [x_k^i - \overline{x_k}]/\sigma_k,\ Z_l^i = [x_l^j - \overline{x_l}]/\sigma_l,$$

where x_k^i is variable *k* at location *i*, x_k^i is observation *l* at location *j*, and σ_k and σ_l are the variance of x_k and x_l, respectively.

Component	1	2	3	4	5
M1	0.830*	0.129	0.346	-0.017	-0.098
M2	0.852*	0.116	0.243	-0.021	-0.073
M3	0.219	-0.105	0.491*	-0.250	-0.019
M4	-0.145	0.265	0.029	0.464*	-0.360
M5	0.047	-0.325	0.743*	0.046	0.058
P1	0.778*	0.375	-0.254	0.069	0.077
P2	0.772*	-0.249	-0.227	-0.041	0.115
P3	0.103	0.860*	-0.163	0.123	-0.040
P4	-0.044	-0.569	0.417*	0.035	-0.104
P5	-0.236	-0.723	-0.148	-0.097	0.111
R1	-0.082	0.182	0.779*	0.104	0.035
R2	-0.089	0.731*	-0.015	-0.151	0.156
R3	-0.035	0.120	0.056	0.056	0.905*
R4	0.073	-0.115	-0.006	0.857*	0.120
Sum of Squared Loadings	2.776	2.601	1.922	1.084	1.051
Explained Variance (%)	19.827*	18.575*	13.732*	7.744	7.505
Explained Variance (%)	19.827	38.402	52.134	59.878	67.383
KMO	0.576				
Bartlett's Test	Degrees of Freedom: 91, Significance: 0.000				

Table 3: Rotated Component Matrix of Gentrification

4 RESULTS

4.1 Principal Component Analysis of Gentrification Composite Indicators

This study used Principal Component Analysis (PCA) on 14 collected gentrification indicators. The results are shown in Table 15, which yielded five principal components, explaining 19.827%, 18.575%, 13.732%, 7.744%, and 7.505% of the variance, respectively (Table 3). This study used principal components with variance greater than 10% as the basis for classifying gentrification indicators. Table 16 summarizes the framework of the composite indicators. Based on the indicator properties of each group, the composite indicators are defined as "Undergoing Gentrification," "Gentrified," and "Upward-filtering Effect." The subsequent spatial analysis results will explain the common results of gentrified areas in the three composite indicators (Table 4).

Composite Indicator	Undergoing Gentrification (Component 1)	Gentrified (Component 2)	Upward-filtering Effect (Component 3)
Indicators	M1 – Total number of immigrants M2 – Total number of emigrants P1 – Percentage of high-income population P2 – Percentage of low-income population	P3 – Percentage of highly educated population R2 – Housing rent price	M3 – Change rate of high-income population M5 – Change rate of highly educated population P4 – Percentage of young and middle-aged population R1 – Real estate transaction volume
Weights	2.776	2.601	1.922

Table 4: Gentrification Composite Indicators

The indicator values of each spatial unit were multiplied by the component loadings of that indicator to perform weighting, and the 'composite indicator score' of that spatial unit in the composite indicator was obtained. Fig. 2 below shows the mapping results of the composite indicators after weighting:

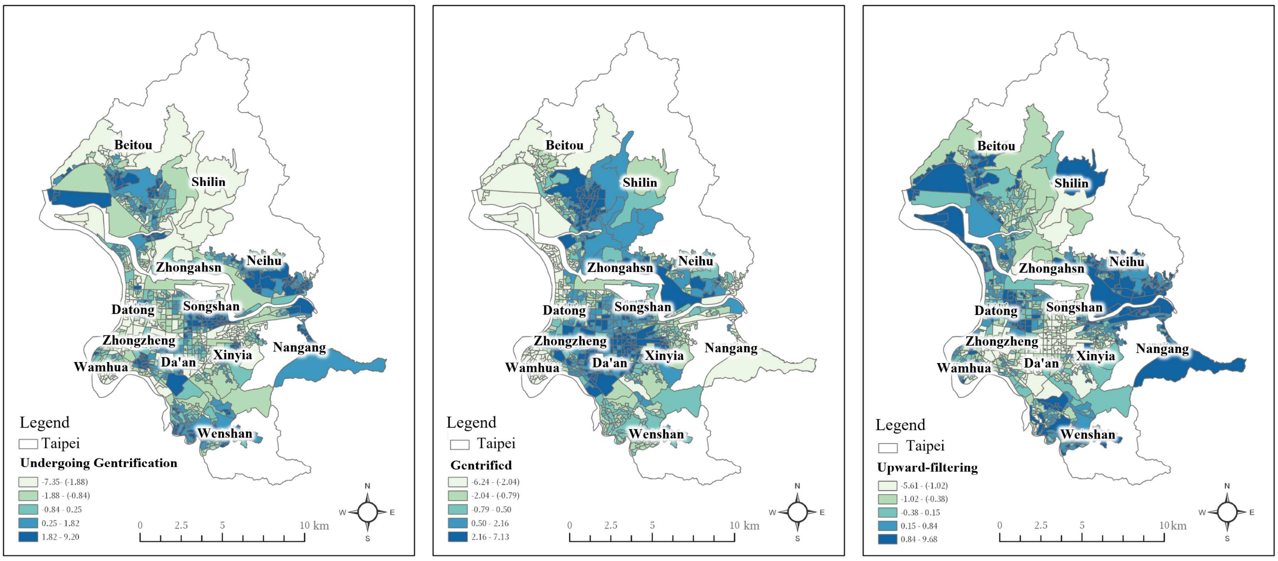

Fig. 2: Mapping of Composite Indicators – Gentrification Patterns

4.2 Spatial correlation of gentrification indicators

To verify whether the gentrification composite indicators have a global spatial autocorrelation aggregation phenomenon, Moran's I was used as the verification method, and the results are shown in Table 17 below. Among them, the P-value is 0 and the Z-scores are all greater than 1.96, which means that all three composite indicators are 'significantly clustered' in the verification results (Table 5):

	Undergoing Gentrification (Component 1)	Gentrified (Component 2)	Upward-filtering Effect (Component 3)
Moran's Index:	0.271455	0.630205	0.394249
Expected Index:	-0.001129	-0.001129	-0.001129
Variance:	0.000047	0.000047	0.000047
z-score:	39.663892*	91.791183*	57.697443*
p-value:	0.000000*	0.000000*	0.000000*

Table 5: Global Spatial Autocorrelation Results of Gentrification Composite Indicators

To use the regional spatial autocorrelation method to find the location of internal spatial clustering of each composite indicator. The results of the "Gentrification Pattern – Regional Spatial Correlation Index" calculated by LISA are as follows (Fig. 3). As can be seen from Figure 32, the High-High values of 'Undergoing Gentrification' are mainly located in the south of Beitou District, the intersection of Songshan District, Da'an District and Zhongzheng District, Neihu District, and Wenshan District; the High-High values of "Gentrified" are mainly located in large areas of Zhongzheng, Songshan, and Da'an Districts, and Shilin District; the High-High values of "Upward-filtering Effect" are located in Beitou District, along the Datong District to Shezidao line, and Neihu District.

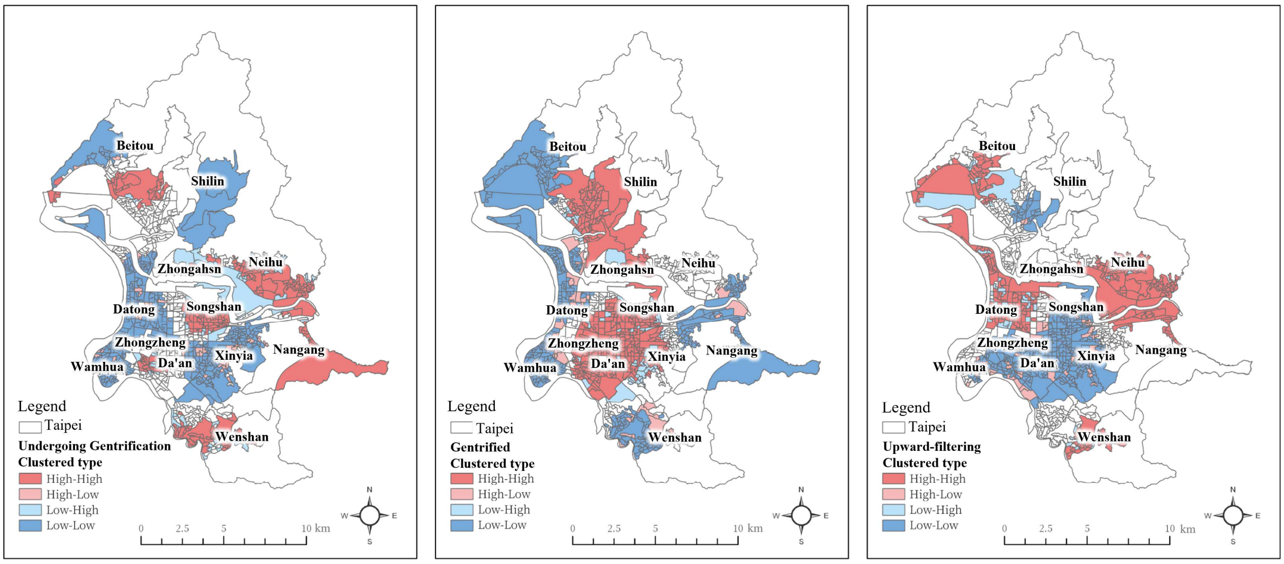

Fig. 3: Spatial Clustering Distribution of Each Gentrification Pattern

4.3 Comparative Analysis of Financial precarity in Gentrified and Upward-filtering Neighborhoods

Given that the principal components of the Upward-filtering areas did not include R2 housing rent prices, and as the figures illustrate a clear divergence in the spatial clustering distribution of the high-value areas between gentrified (Principal Component 2) and Upward-filtering effects (Principal Component 3), a subsequent analysis was conducted to examine the characteristics of financial precarity within these distinct high-value (HH) areas.

This study investigates the nuanced dynamics of financial precarity within urban areas undergoing socio-economic transformation. Specifically, we compare and contrast two distinct neighborhood types: those experiencing gentrification and those exhibiting a Upward-filtering effect. Gentrification, characterized by the influx of higher-income residents and subsequent displacement of existing populations, often leads to significant changes in the social and economic fabric of a neighborhood. The Upward-filtering effect, while also involving an influx of more affluent individuals, may not necessarily result in direct displacement but rather a gradual shift in the area's character and affordability.

The analysis focuses on key indicators of financial precarity, examining how these manifest differently in gentrified versus filtering-up neighborhoods.

4.3.1 Analysis of financial precarity variables in Gentrified HH Areas and Upward-filtering HH Areas

A comparative overview of these indicators in gentrified and Upward-filtering high-value (HH) areas reveals notable differences (Table 6).

(A) Change Rate of High-Income Population(M3):

The mean value of M3 is negative in both gentrified and Upward-filtering areas, suggesting a general trend of high-income population decrease. However, the magnitude of decrease is smaller in Upward-filtering areas (-1.29) compared to gentrified areas (-2.61). This may indicate that while both area types experience some level of high-income population loss, Upward-filtering areas are relatively more stable in attracting and retaining affluent residents. The higher standard deviation in Upward-filtering areas (1.18 vs. 1.06) suggests a greater variability in the change rate of high-income population, potentially reflecting a more dynamic economic environment.

Indicator	Gentrified HH Areas	Upward-filtering HH Areas	Remaining Areas
Mean M3	-2.61	-1.29	-2.5335
Standard Deviation M3	1.06	1.18	1.13820
Mean M5	0.79	1.7	1.1284
Standard Deviation M5	0.55	0.79	0.72114
Mean R1	124.28	184.62	113.2759
Standard Deviation R1	69.58	182.73	82.36377
Mean R2	47500.24	30218.63	28997.7741
Standard Deviation R2	12942.61	10259.75	10557.86973

Table 6: Observations of Financial Precarity Variables in Gentrified HH Areas and Upward-filtering HH Areas

(B) Change Rate of Highly Educated Population (M5):

The mean value of M5 is positive in both gentrified and Upward-filtering areas, indicating an overall increase in the highly educated population. Notably, the mean value is substantially higher in Upward-filtering areas (1.70) compared to gentrified areas (0.79). This suggests that Upward-filtering areas experience a more pronounced influx of highly educated individuals. The standard deviation is also higher in Upward-filtering areas (0.79 vs. 0.55), implying a greater range of variation in the change rate of the highly educated population.

(C) Real Estate Transaction Volume(R1):

The mean real estate transaction volume (R1) is significantly higher in Upward-filtering areas (184.62) than in gentrified areas (124.28), indicating a more active real estate market. The standard deviation is also considerably higher in Upward-filtering areas (182.73 vs. 69.58), suggesting greater volatility in real estate transactions. This may reflect increased speculative activity and rapid neighborhood change in Upward-filtering areas.

(D) Housing Rent Price(R2):

The mean housing rent price (R2) is substantially higher in gentrified areas (47500.24) than in Upward-filtering areas (30218.63). This is consistent with the conventional understanding of gentrification as a process that drives up housing costs. However, the standard deviation is also higher in gentrified areas (12942.61 vs. 10259.75), implying a wider range of rent price variation.

4.3.2 Correlation analysis of financial precarity variables between Gentrified HH Areas and Upward-filtering HH Areas

Furthermore, an examination of correlations between these variables provides insights into the interconnectedness of financial precarity factors in HH Areas(Table 7):

Indicator	Gentrified HH Areas	Upward-filtering HH Areas	Remaining Areas
Correlation between M3 and M5	0.226**	0.106	0.117*
Correlation between M3 and R1	0.123*	0.116	0.026
Correlation between M3 and R2	-0.028	0.049	0.165**
Correlation between M5 and R1	0.382**	0.393**	0.343**
Correlation between M5 and R2	0.069	0.021	-0.066
Correlation between R1 and R2	0.075	0.267**	0.035

Table 7: Correlation of Financial Precarity Variables in Gentrified HH Areas and Upward-filtering HH Areas

(A) Correlation between M3 and M5:

In both gentrified and Upward-filtering areas, there is a positive correlation between the change rate of high-income population (M3) and the change rate of highly educated population (M5). This suggests that areas experiencing an influx of high-income residents also tend to attract highly educated individuals. However, the correlation is stronger in gentrified areas (0.226**) compared to Upward-filtering areas (0.106).

(B) Correlation between M5 and R1:

A strong positive correlation between the change rate of highly educated population (M5) and real estate transaction volume (R1) is observed in both gentrified (0.382**) and Upward-filtering areas (0.393**). This indicates a close relationship between the influx of highly educated individuals and increased real estate market activity.

(C) Correlation between R1 and R2:

Notably, the correlation between real estate transaction volume (R1) and housing rent price (R2) is substantially stronger in Upward-filtering areas (0.267**) compared to gentrified areas (0.075). This suggests that in Upward-filtering areas, changes in real estate market activity have a more direct impact on rent prices.

4.3.3 Bivariate spatial autocorrelation analysis

This study further employs bivariate spatial autocorrelation analysis to investigate the spatial clustering patterns of correlated variables within Gentrified and Upward-filtering HH Areas. This approach allows for the observation of how the spatial distribution of one variable relates to the spatial distribution of another, providing insights into the geographic co-location of socio-economic changes.

The spatial autocorrelation analysis reveals distinct patterns in the relationships between key socio-economic variables across gentrified and Upward-filtering neighborhoods. The significant positive spatial autocorrelation between M3 (high-income population change) and M5 (highly educated population change) suggests a strong spatial linkage between these demographic shifts, with areas experiencing changes in one group tending to experience corresponding changes in the other. This pattern is particularly pronounced in gentrified areas (Table 8).

Furthermore, the positive spatial autocorrelation between M5 and R1 (real estate transaction volume) in both neighborhood types underscores the connection between human capital influx and real estate market activity. Areas attracting highly educated individuals also tend to experience increased real estate transactions, potentially reflecting speculative investment and development pressures.

However, while a statistically significant correlation was found between R1 and R2 (housing rent price) in earlier analysis, the lack of significant spatial autocorrelation suggests that this relationship is not uniform across space. Localized factors, such as zoning or housing policies, may play a more influential role in rent price variation, highlighting the importance of considering both correlation and spatial relationships in examining neighborhood change.

	M3 and M5	M5 and R1	R1 and R2
Moran's Index:	0.269	0.136	-0.0058
Expected Index:	-0.0011	-0.0011	-0.0011
z-score:	16.2337	8.3257	-0.3975
p-value:	0.001*	0.001*	0.37200

Table 8: Bivariate Spatial Autocorrelation Results of Financial Precarity Variables in Gentrified HH Areas and Upward-filtering HH Areas

The analysis reveals that HH areas characterized by high values of both M3 (change rate of high-income population) and M5 (change rate of highly educated population) are predominantly concentrated within Upward-filtering HH Areas (Fig. 4). This suggests that the influx of both high-income individuals and highly educated residents tends to occur in the same geographic locations, specifically within areas experiencing the filtering-up effect. Conversely, LL areas with low values for both M3 and M5 are more frequently clustered within Gentrified HH Areas. This may indicate that areas undergoing gentrification experience a relative decline in both high-income and highly educated residents, potentially due to displacement pressures and affordability challenges.

Furthermore, HH areas exhibiting high values for both M5 (change rate of highly educated population) and R1 (real estate transaction volume) are also largely concentrated within Upward-filtering HH Areas. This finding underscores the strong connection between the influx of highly educated individuals and heightened real estate market activity in these areas (Fig. 4).

5 CONCLUSION

This study examined gentrification and upward filtering dynamics in Taipei City, focusing on financial precarity and displacement. Principal component analysis identified three neighborhood change patterns: “Undergoing Gentrification”, “Gentrified”, and “Upward-filtering Effect”, each with significant spatial clustering. "Gentrified" areas saw declining high-income and highly educated residents, potentially due to displacement. “Upward-filtering Effect” areas attracted more of these groups, coupled with increased real estate transactions.

Comparative analysis revealed further distinctions. While both area types experienced demographic and real estate shifts, the strength and spatial relationships varied. The correlation between real estate transaction volume and rent prices was stronger in upward-filtering areas, indicating a more direct impact on affordability. However, the lack of significant spatial autocorrelation suggests localized factors like zoning influence rent price dynamics.

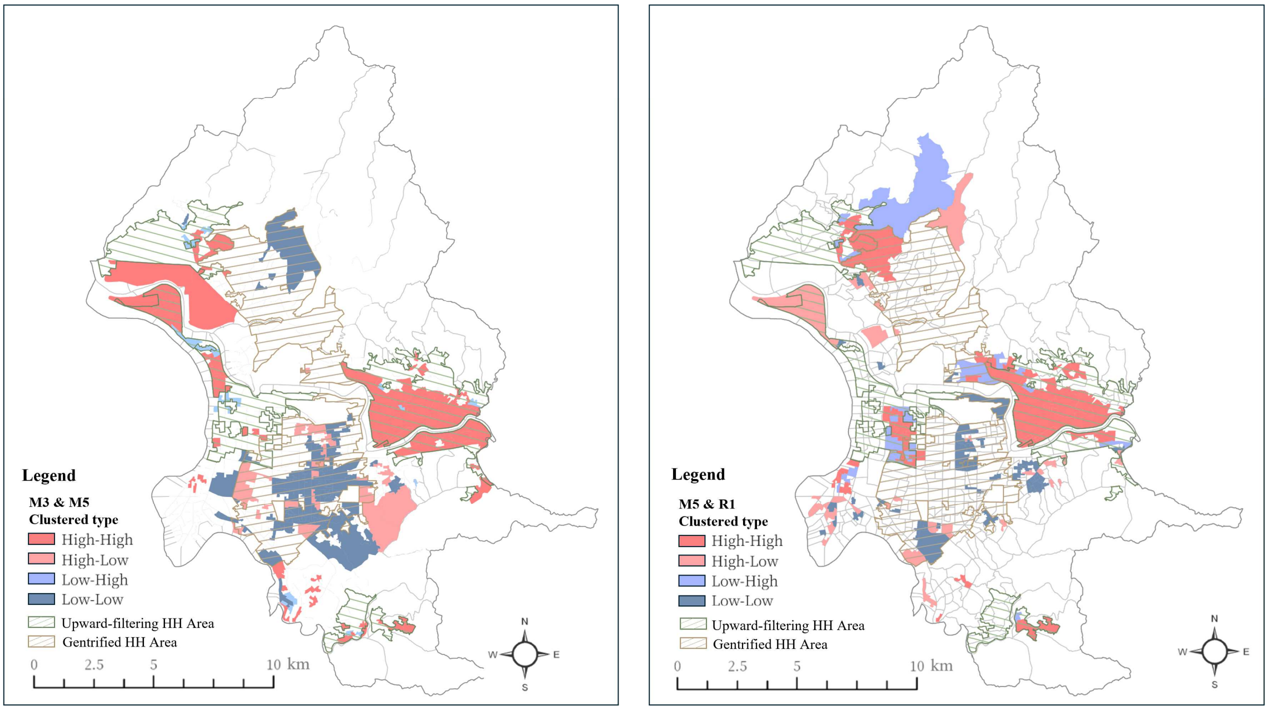

Fig. 4: Spatial Clustering Distribution of Financial Precarity Variables with Gentrified HH Areas and Upward-filtering HH Areas

Bivariate spatial autocorrelation revealed spatial linkages. The clustering of areas with high rates of change in high-income and highly educated populations in upward-filtering areas reinforces the interconnectedness of these shifts. Similarly, high rates of change in the highly educated population and real estate transaction volume highlight the connection between human capital and real estate activity. These findings contribute to a nuanced understanding of gentrification and upward filtering, emphasizing the need for policies mitigating financial precarity and displacement while promoting equiable urban development. Future research could explore targeted interventions to address these challenges.

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