The relationship between urban planning and housing price resilience: A study of urban flooding events

Wang Kuan-Fei[1] **Hsiao Chia-Yi**[2]

Abstract

This study investigates whether flood records over the past decade in the Shilin, Zhongshan, and Da'an districts of Taipei City have affected residential prices. It uses actual transaction data from January 2013 to October 2023, combined with flood records from 2013 to 2023, as reported by the Taipei City Hydraulic Engineering Office. "The analysis was conducted using quantile regression and spatial quantile regression combined with the difference-in-differences method. The results show that for each additional flood record before the transaction, the total house price increased by 1.1% in Shilin District, 1.5% in Zhongshan District, and 0.5% in Da'an District. For each centimeter increase in the depth of the previous flood record, the total house price decreased by 1.5% in Shilin District, increased by 0.1% in Zhongshan District, and decreased by 1.1% in Da'an District. These results are more significant for high-priced houses in Shilin District, mid-to-high-priced houses in Zhongshan District, and mid-to-low-priced houses in Da'an District.

Keywords: urban resilience, housing, difference-in-difference method, spatial quantile regression

1. Introduction

Due to the impact of global climate change, many cities have experienced an increase in extreme weather events such as floods, tornadoes, earthquakes, tsunamis, and wildfires (Salinger,2005). In the face of natural disasters, cities often demonstrate resilience by recovering to their pre-disaster state, showcasing their ability to withstand and adapt to such challenges (Rolf Pendall et al., 2008). In the aftermath of disaster events, in addition to the reconstruction of infrastructure, the recovery of the economy is also a key focus for many people. Therefore, strengthening urban resilience and enhancing economic robustness are issues that city planners and policymakers should prioritize. This not only helps to mitigate the impact of flooding events on cities and their residents but also contributes to improving the overall resilience and sustainability of urban areas. In recent years, Taiwan has faced challenges to its urban infrastructure due to heavy rains and typhoons. In highly urbanized areas, despite well-developed infrastructure, increased development intensity and the rise of impermeable surfaces have prevented rainwater from draining efficiently, leading to flooding. During the process of urbanization, the development of roads and buildings increases the amount of impermeable surfaces, which reduces the city's infiltration rate and raises the risk of flooding. Taiwan's urban planning mandates the designation of land for public facilities, including parks, green spaces, and plazas, requiring that these areas occupy no less than ten percent of the total planned area. In urban areas, green

[1] University of Taipei, kfei.wang@utaipei.edu.tw
[2] University of Taipei, G11250002@go.utaipei.edu.tw

spaces not only mitigate urban runoff and the heat island effect (Zhang, 2017), but they are also typically regarded as desirable amenities in the real estate market. Peng (2005) suggests that for every additional hectare of green coverage within a radius of 500 meters, housing prices may increase by approximately 20,000 yuan. This indicates that urban green spaces not only alleviate urban flooding but also serve as a contributing factor to the appreciation of real estate prices. After flooding events, housing prices typically experience an impact, but the stronger the urban resilience, the higher the resilience of property prices. Additionally, the recovery speed is likely to be faster. Tobin and Montz's (1994) research found that flooding typically has an average impact of around 15% on property transactions. However, after repair work is completed, property prices in flooded areas may even rise.

Resilience was first proposed in ecological research as the capacity of an ecosystem to absorb change and disturbance while still maintaining its basic functions (Holling, 1973). The definition of disaster resilience refers to the ability of individuals, organizations, systems, or communities to cope with, face, or adapt to the impacts of environmental changes or disasters, allowing them to recover or return to a state close to their original condition. Economic resilience refers to the capacity of an economic system to withstand shocks. It is defined as the ability of an economy to respond to disasters and disturbances, including its inherent capacity to avoid negative impacts, withstand changes in the economic development environment, and maintain its original economic level (Hung, 2023). Kyungsoon Wang (2019) defines housing market resilience as the ability of the market to recover relatively quickly from shocks and to maintain a relatively stable state after the shock.

An urban system is composed of many elements, including land use in urban planning and the real estate market's economic activities. As the capital of Taiwan, Taipei boasts excellent urban planning and consistently high housing prices. However, urban water management remains a significant challenge for the city. In recent years, heavy rainfall events have frequently caused flooding in the Taipei metropolitan area. This study views urban flooding as an external factor that disrupts the urban system. Using residential prices in the real estate market as a research basis, it defines the internal and external variables that contribute to housing price resilience. Additionally, it explores whether different urban planning measures can enhance housing price resilience after flooding events. Finally, the study provides policy recommendations based on these findings.

(1) Exploring the Internal and External Variables that Contribute to Housing Price Resilience

(2) Do Differences in Urban Planning Contribute to Housing Price Resilience After Flooding?

(3) Provide Relevant Policy Recommendations

This study comprises four parts. The first part involves a literature review and analysis to identify and define the variables influencing housing price resilience. The second part uses the difference-in-differences method to distinguish between the experimental and control groups in the research model. The third part employs a spatial quantile regression model to empirically analyze the combination of land use variables affecting housing prices. Finally, based on the results and incorporating the perspective of resilient cities, the study provides relevant policy recommendations.

2. Resilient urban planning and housing price

Resilience originates from the Latin root *'resi-lire*,' meaning 'to spring back.' It was initially used by physical scientists to describe the characteristics of springs and to denote the stability of materials and their resistance to external shocks (Davoudi, 2012). Resilience originated from Holling's (1973) ecological research concept, defining it as the ability of a system to maintain stable structure and function when faced with disturbances or changes. In the face of climate change threats and future uncertainties, the concept of resilience has garnered interest from scholars across multiple disciplines and fields. Subsequently, this concept was extended to engineering (Holling, 1996; Carpenter et al., 2001), economics (Rose, 2007), and the field of planning (Ahern, 2011). The planning field, considered closely related to sustainable urban development, focuses on the adaptive design of urban physical systems and urban biodiversity. This requires complementary interdisciplinary research (Ahern, 2011).

As the number of people living in cities increases, the scale of urban risks continues to grow. Due to the complexity of urban systems and the associated uncertainties, these risks are becoming increasingly difficult to predict (The Rockefeller Foundation,2015). Hall et al. (2018) conducted an in-depth study of the U.S. housing market and found that urban resilience significantly impacts housing prices. Cities with higher resilience tend to maintain housing price stability more effectively. Additionally, natural disasters are a key factor influencing housing prices. Urban resilience can boost investor confidence in the real estate market, stabilizing the market not only for local residents but also attracting foreign investors. Tian et al. (2021) observed the resilience of the real estate market in China's Yangtze River Delta region in the aftermath of the COVID-19 pandemic. The results indicated that cities less affected by the pandemic recovered more quickly, and the rate of increase in housing prices was proportional to the level of impact.

The Intergovernmental Panel on Climate Change (IPCC) believes that reducing risk through zoning and land use can effectively protect and expand green infrastructure, mitigating flood hazards and reducing the urban heat island effect. In 2011, the United Nations ranked Taipei as the third most threatened city globally facing more than three types of disasters (World Urbanization Prospects: The 2011 Revision). Spatial planning is a crucial approach to enhancing disaster resilience. Land planning is the starting point for spatial planning and governance, and through appropriate land use allocation and development management, it can provide a disaster-resistant environment, thereby reducing the impact of disasters and shortening the recovery period (Chen Liangquan & Zhan Shiliang, 2020). The development goals of Taipei City's land use planning focus on strengthening conservation and urban resilience. This includes cross-domain integration of urban disaster prevention and mitigation responses to enhance urban climate adaptation capabilities. This aligns with urban planning and design efforts to implement the concept of Low Impact Development (LID) (Taipei City Land Use Zoning Plan Explanation, 2021).

Property values are determined not only by their own characteristics but also by factors such as community socioeconomic status, land use patterns, and environmental features (Acharya & Bennett, 2001). Disasters can lead to declines in housing prices, but effective urban planning can contribute to price increases. Analyzing the impact of flooding events and land use on housing prices can provide deeper insights into the factors behind price fluctuations. When facing flood risks, this analysis can assist urban planners in formulating more effective disaster prevention measures and real estate market regulatory policies. This in turn enhances urban resilience, protects residents' asset values, and promotes sustainable urban development.

Lee (2001) studied the impact of residential zoning on land prices in Taipei City. According to planning intentions, it is believed that residential Zone 1 should have the highest quality of living environment, while Zone 4 should have the lowest. This is because higher plot ratios lead to high-density development, which can lower environmental quality. However, higher plot ratios also tend to increase land prices due to the diversity of uses landowners may prefer. For planners, creating high-quality residential neighborhoods may require reducing statutory plot ratios. Wu (2008) studied the impact of plot ratio on housing prices in Taipei City. The results showed that total housing prices are influenced by factors such as building area, age of the building, statutory plot ratio, and distance to the nearest MRT station. For every 1% increase in statutory plot ratio, housing prices on average increase by 0.017%. However, an increase of 1% in the floor area ratio of the building's block has a negative impact, reducing housing prices by approximately 0.008%, due to crowding externality effects on local residents. G. Donald Jud (1980) studied the impact of zoning on single-family residential housing prices across 3,513 households in the United States. The model factors in zoning classification, neighborhood land use patterns, neighborhood socioeconomic conditions, structural quality, building size, and lot size. Residential zoning increases the value per square foot by 11%, while commercial activities lead to a price discount of approximately 12%.

Lei Zhang (2016) investigated the impact of the 2009 flood disaster on high-priced and low-priced houses, while also considering spatial autocorrelation. The results showed that the disaster had a greater impact on low-priced houses, causing an overall price discount of 4% to 12%. One year after the flood, the reaction from homebuyers was the most significant, and two years later, the price decline effect caused by the flood had disappeared. Rajapaksa et al. (2017) analyzed the spatial and temporal impacts of the 2011 Brisbane flood on the real estate market. The results showed that overall housing prices decreased by 5%. Prices in high-income suburbs began to recover two years after the flood, while prices in low-income suburbs continued to decline. Despite the flood risk, people tend to live near rivers because the land is cheaper and the amenities (such as waterfront views or scenery) outweigh the flood risk. Additionally, the government's publication of risk maps allows residents to take appropriate measures, ultimately leading to an increase in regional prices. Lee et al. (2020) explored whether the publication of flood potential maps in Taipei City would impact housing prices. After the release of the rainfall flood simulation maps, residential prices in flood-prone areas decreased by 13.5%, with the effect being most pronounced for high-priced homes, which saw a decline of approximately 19.3%. However, residential prices in areas adjacent to the flood zones did not show a significant decrease.

When purchasing real estate, people typically refer to past flooding events and flood potential maps to predict the likelihood of future occurrences. These records often directly affect the value of properties (Li Chunchang et al., 2020; Bin et al., 2008). However, this impact may gradually diminish over time as people's memory of the floods fades (Bin et al., 2011; Rajapaksa et al., 2017). Despite the flood risk, areas with more facilities tend to recover faster than those with fewer facilities (Rajapaksa, 2016). The speed and scale of value recovery depend on various socioeconomic and environmental characteristics. Current flood mitigation strategies are primarily divided into two major categories: structural mitigation and non-structural mitigation measures. In the last century, most countries commonly used structural mitigation methods to counter flood threats, including the construction of levees and dams. However, relying solely on engineering measures for disaster mitigation can paradoxically increase long-term flood risks, leading to the levee effect.

Non-structural mitigation measures mainly include financial and planning strategies. Financial strategies encompass rent and insurance (Yu-Shou Su, 2015). The U.S. Congress established the National Flood Insurance Program (NFIP) in 1968 to mitigate the impact of floods on people and physical capital. Part of the motivation for providing insurance was to internalize the costs of occupying flood-prone areas and reduce public spending on flood response and recovery (Bin & Landry, 2013). Planning strategies primarily focus on land use planning and management. Rapid urbanization has led to an increase in impervious surfaces, with a 10-20% increase in impervious surfaces within a watershed roughly doubling the runoff volume (Arnold and Gibbons, 1996). Therefore, land use and environmental planning that emphasize water retention areas and permeable surface design will provide strategies to reduce flood risk (Yu-Shou Su, 2015). The characteristics of land use influence flood risk, which in turn severely impacts land use efficiency. Urban economic development and population growth drive the expansion of built-up areas and frequent human interventions within riverbeds, exacerbating urban flooding (Fang Wei & Lvwang Zha, 2022). From the perspective of landscape ecology, Liu (2018) explored the relationship between land use patterns and flood potential in Taichung City. The study indicated that built-up areas, agricultural land, and transportation land use types have the most significant impact on flooding. Additionally, areas with more diverse land use patterns tend to experience less severe flooding.

In the field of real estate research, the impact of flood events and land use on property prices has long been an important topic. This study employs two methods, namely Difference-in-Differences (DiD) and Spatial Quantile Regression (SQR), to comprehensively investigate the effects of flood events and land use on property prices. Difference-in-Differences (DiD) methodology effectively controls for temporal and spatial variations, thereby enhancing the accuracy and credibility of the research. On the other hand, Spatial Quantile Regression (SQR) better captures spatial dependence and effectively handles the characteristics of spatial data. By integrating these two methods, this study aims to provide a deeper understanding of the mechanisms through which flood events and land use influence property prices.

Difference-in-Differences (DiD) methodology is commonly used to assess changes before and after specific events or policy implementations. This method assumes two groups: the treatment group and the control group. The treatment group is affected by the event or policy change, while the control group remains unaffected. By comparing these two groups, DiD aims to observe the differences in outcomes attributed to the occurrence of the event or implementation of the policy (Li et al., 2020). In traditional regression models, outliers can significantly impact the results. Moreover, in linear models with non-Gaussian errors, there may be serious shortcomings as well. Therefore, Koenker and Bassett (1978) proposed quantile regression models, which can provide insights into the middle and tail sections of the conditional distribution. This approach helps understand how explanatory variables affect the response variable across different quantiles. The estimated results are also more robust and suitable for interpreting and analyzing the data. Lei Zhang

(2016) integrated quantile regression with difference-in-differences and spatial econometric models to study the impact of flood events on housing prices in the United States. Spatial quantile regression models allow for estimating the differential effects of flood disasters on the conditional distribution of housing prices. Spatial variables capture spatial dependence and spatial heterogeneity in the housing market. Therefore, using this model enables studying the impact of flood disasters on the entire distribution of housing prices while accounting for spatial effects.

3. Data and Methods

3.1 Data

Through a resilient city perspective, this study examines the impact of flooding events on housing prices and evaluates urban planning's capacity to facilitate the recovery of housing prices post-flooding. Effective urban planning recommendations will be proposed based on the analysis of flooding data and real estate information from Taipei City spanning from 2013 to 2023. The Taipei City Hydraulic Engineering Office established the "Taipei City Flood Information Network" in 2016 under the principles of information transparency. This network compiles historical records of flooding events where water accumulation exceeded 15 centimeters. The publicly available information includes locations, causes, timing, and depth of flooding. Additionally, since 2012, the Ministry of the Interior has implemented the Real Estate Transaction Information Disclosure System, aimed at enhancing transparency in the real estate market and addressing information asymmetry issues. This system requires the disclosure and registration of actual transaction details. Observing the past decade (2013-2023), the areas in Taipei City with the highest to lowest frequencies of flooding events are Shilin District, Da'an District, and Zhongshan District.

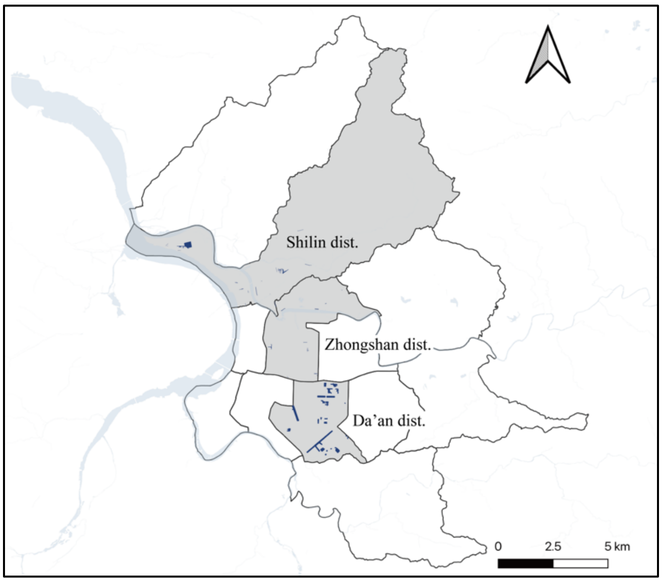

Figure 1 Division of Taipei City into Zones and Distribution Map of Flooding

3.2 Methods

To investigate the impact of flooding events on housing prices, we first apply the Difference-in-Differences (DiD) method, setting properties within 300 meters of flood-affected areas as the treatment group, and properties within 300 meters of areas unaffected by flooding as the control group. In this study, the dependent variable is the total transaction price of the houses, while the independent variables include individual characteristic for example: building area, age and type of property; resilient city indicator variables including floor area ratio, building coverage ratio, fore yard width, rare yard width, excavation rate, distance to the nearest MRT station and distance to the nearest green space; macroeconomic characteristics including the annual adjustment rate of current land value, annual growth rate of the number of transactions and interest rate; Lastly, in the explanatory variables, we include the number of flooding and the depth of flooding. And the experimental and control groups for the difference-in-differences method, with the quantile regression model specified as equation (1)

$$\ln P_{it}=\beta_1(\theta)+\beta_2(\theta)AREA+\beta_3(\theta)AGE+\beta_4(\theta)TYPE+\beta_5(\theta)FAR+\beta_6(\theta)BCR+\beta_7(\theta)FYW+\beta_8(\theta)RYW +\beta_9(\theta)ER+\beta_{10}(\theta)DISGR+\beta_{11}(\theta)DISMRT+\beta_{12}(\theta)AR+\beta_{13}(\theta)BGR+\beta_{14}(\theta)IR+\beta_{15}(\theta)FNM+\beta_{16}(\theta)FD+\beta_{17}(\theta)TREARMENT_i+(\theta)\sigma_{it.} \quad (1)$$

Furthermore, referring to Liao & Wang (2012), incorporate spatial econometrics into a two-stage spatial quantile regression model, adding spatial lag variables W1nP in Equation (1), W is Spatial Weights and ρ is Spatial autocorrelation coefficient, represent the spatial quantile regression model using equation (2). The first stage involves using the independent variables as explanatory variables in quantile regression, estimated fitted values $\ln\hat{}P$, in the second stage, substitute W1nP back into equation (2) for estimation.

$$\ln P_{it}=\rho W\ln\hat{}P+\beta_1(\theta)+\beta_2(\theta)\mathrm{AREA}+\beta_3(\theta)\mathrm{AGE}+\beta_4(\theta)\mathrm{TYPE}+\beta_5(\theta)\mathrm{FAR} +\beta_6(\theta)BCR+\beta_7(\theta)FYW+\beta_8(\theta)RYW+\beta_9(\theta)ER+\beta_{10}(\theta)DISGR+\beta_{11}(\theta)DISMRT +\beta_{12}(\theta)AR+\beta_{13}(\theta)BGR+\beta_{14}(\theta)IR+\beta_{15}(\theta)FNM\,\beta_{16}(\theta)FD+\beta_{17}(\theta)TREARMENT_i+(\theta)\sigma_{it.}$$

3.3 Variables Setup

Table 1 Selected variables

	Variable	Symbol	Description	Expected Sign
Dependent variable	Transaction price	*PRICE*	House price in New Taiwan Dollars (TWD)	-
Individual characteristic	Building area	*AREA*	Building area of housing transaction	+
	Age of property	*AGE*	Age of the house in years	-
	Congregate housing	*TYPE*	1= type is congregate housing	+
	Apartment	*TYPE*	1= type is apartment	-
Resilient city indicator variables	Floor area ratio	*FAR*	Floor Area Ratio of the land use zone where the house is located.	+
	Building coverage ratio	*BCR*	Building coverage ratio of the land use zone where the house is located.	-
	Fore yard width	*FYW*	Fore yard width of the land use zone where the house is located.	+
	Rare yard width	*RYW*	Rare yard width of the land use zone where the house is located.	+
	Excavation rate	*ER*	Excavation rate of the land use zone where the house is located.	+

	Distance to green space	*DISGR*	The straight-line distance from the house to the nearest green space, measured in meters.	+
	Distance to MRT station	*DISMRT*	The straight-line distance from the house to the nearest MRT station, measured in meters.	+
Explanatory variables	Number of flooding	*FNM*	The number of flood occurrences before transactions.	-
	Depth of flooding	*FD*	The depth of flooding from the nearest flood event.	-
Macro-economic characteristics	Annual adjustment rate of current land value	*AR*	The annual adjustment rate of the announced land value in Shilin District, Zhongshan District, and Da'an District.	+
	Annual growth rate of the number of transactions	*BGR*	Annual growth rate of the number of transactions in Taipei city	+
	Interest rate	*IR*	Basic loan rate of Central Bank	-

4. Results

Table 2 OLS and quantile regression (QR) results

	OLS	0.1	0.25	0.5	0.75	0.9
			Shilin Dist.			
AREA	0.89 ***	0.574 ***	0.699 ***	0.847 ***	0.97 ***	1.104 ***
AGE	-0.03 ***	-0.024 ***	-0.012 ***	-0.014 ***	-0.02 ***	-0.02 ***
TYPE-B	0.03 ***	0.0009 *	-0.005 ***	0.009 ***	0.04 ***	0.033 ***
TYPE-A	-0.04 ***	-0.04 ***	-0.056 ***	-0.067 ***	-0.073 ***	-0.06 ***
FAR	-0.07 ***	-0.013 **	-0.029 ***	-0.048 ***	-0.061 ***	-0.053 ***
BCR	0.16 ***	0.041 ***	0.087 ***	0.123 ***	0.147 ***	0.132 ***
FYW	0.15 ***	-0.008 *	0.049 ***	0.091 ***	0.128 ***	0.087 ***
RYW	0.02 ***	0.001 *	0.016 ***	0.013 ***	0.011 *	-0.002 *
EXCAVATION	0.02 *	-0.051 ***	-0.02 *	0.003 *	0.027 *	-0.004 *
AR	-0.001 *	-0.009 *	0.002 *	0.007 ***	0.001 *	-0.004 *
BGR	-0.004 *	-0.007 ***	-0.001 *	0.001 **	0.002 *	0.002 *
IR	-0.004 *	-0.002 **	-0.004 *	-0.001 **	0.002 *	-0.001 *
DISMRT	-0.1 ***	-0.07 ***	-0.091 ***	-0.089 ***	-0.071 ***	-0.058 ***
DISGREEN	-0.001 *	-0.003 *	-0.001 *	-0.00006 *	0.003 *	0.004 *
FNM	0.01 ***	0.003 *	0.007 ***	0.008 ***	0.013 ***	0.018 ***
FD	-0.02 ***	-0.009 ***	-0.014 ***	-0.01 ***	-0.014 ***	-0.016 ***
Adjusted/ pseudo R^2	0.878	0.416	0.513	0.606	0.707	0.789
			Zhongshang Dist.			
AREA	0.92 ***	0.66 ***	0.77 ***	0.88 ***	1.00 ***	1.13 ***
AGE	-0.06 ***	-0.05 ***	-0.05 ***	-0.05 ***	-0.05 ***	-0.04 ***
TYPE-B	0.02 ***	0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.01 ***
TYPE-A	-0.01 ***	-0.03 ***	-0.03 ***	-0.02 ***	-0.02 ***	-0.01 ***
FAR	0.01 **	0.01 *	-0.002 *	0.006 *	-0.003 **	-0.01 ***
BCR	-0.4 ***	-0.07 ***	-0.12 ***	-0.16 ***	-0.1 ***	-0.06 ***
FYW	-0.73 ***	-0.03 *	-0.12 ***	-0.19 ***	-0.16 ***	-0.13 ***

	OLS	0.1	0.25	0.5	0.75	0.9
RYW	-0.09 ***	0.004 *	-0.01 ***	-0.02 ***	-0.01 ***	-0.007 ***
EXCAVATION	-0.36 ***	0.02 *	-0.0003 *	-0.04 ***	-0.06 ***	-0.06 ***
AR	-0.001 *	0.003 *	0.004 ***	0.004 ***	-0.006 ***	-0.01 ***
BGR	-0.005 ***	0.002 *	0.001 *	-0.0002 *	-0.004 ***	-0.006 ***
IR	-0.007 ***	-0.02 ***	-0.01 ***	-0.01 ***	-0.0007 *	0.003 **
DISMRT	-0.04 ***	-0.01 ***	-0.02 ***	-0.03 ***	-0.03 ***	-0.02 ***
DISGREEN	0.005 ***	0.003 **	0.0008 *	-0.0008 *	0.0007 *	0.00008 *
FNM	0.01 ***	-0.006 ***	0.0007 *	0.005 ***	0.006 ***	0.006 ***
FD	-0.0007 *	0.005 ***	-0.001 *	-0.002 **	-0.004 ***	-0.004 ***
Adjusted/ pseudo R^2	0.93	0.561	0.651	0.727	0.793	0.848
			Da'an Dist.			
AREA	0.92 ***	0.765 ***	0.91 ***	1.035 ***	1.16 ***	1.32 ***
AGE	-0.04 ***	-0.009 ***	-0.018 ***	-0.027 ***	-0.03 ***	-0.036 ***
TYPE-B	0.042 ***	-0.003 *	-0.017 ***	-0.007 ***	0.005 ***	0.005 **
TYPE-A	-0.057 ***	-0.051 ***	-0.051 ***	-0.047 ***	-0.043 ***	-0.043 ***
FAR	0.008 *	0.03 ***	0.03 ***	0.015 ***	0.014 ***	0.014 *
BCR	0.07 ***	0.04 ***	0.064 ***	0.05 ***	0.016 ***	-0.003 *
FYW	- -	0.058 ***	0.087 ***	0.064 ***	0.028 ***	0.001 *
RYW	0.031 ***	0.021 ***	0.033 ***	0.027 ***	0.013 ***	0.001 *
EXCAVATION	-0.1 ***	- -	- -	- -	- -	- -
AR	0.009 ***	0.006 ***	0.017 ***	0.014 ***	0.011 ***	0.009 ***
BGR	-0.004 *	0.001 *	0.003 **	-0.0003 *	-0.004 ***	-0.001 *
IR	-0.004 *	0.0008 *	-0.0001 *	0.004 **	0.007 ***	0.008 ***
DISMRT	0.029 ***	0.006 ***	0.006 ***	0.005 ***	0.004 ***	0.001 *
DISGREEN	-0.011 ***	0.006 ***	0.007 ***	0.005 ***	0.001 *	0.004 **
FNM	0.012 ***	0.02 ***	0.023 ***	0.011 ***	0.009 ***	0.011 ***
FD	-0.004 *	0.005 *	-0.003 *	0.002 *	0.001 *	0.0006 *
Adjusted/ pseudo R^2	0.895	0.524	0.59	0.658	0.729	0.797

Based on Table 2, the OLS results estimated by the least squares method are significant, with R-squared values of 0.878, 0.930, and 0.895 for the three districts, indicating a goodness of fit of the model. First, the OLS estimation results show that the coefficient estimates for building area are 0.89 and 0.92, significant at the 1% level, indicating that for every one ping increase in area, the total residential price increases by 89% (Shilin District) and 92% (Zhongshan and Da'an District). If the building type is congregate housing, it will also have a positive correlation with the price, with an impact of approximately 2% to 4% across the three districts. Age and building type (apartment) exhibit negative correlations with individual residential characteristics. An increase in age by one year results in approximately a 3% to 6% decrease in housing prices across the three districts. Regarding the resilience city index variables, FAR has a negative impact of 7% on residential prices in Shilin District, but shows positive correlations of 1% and 0.8% for Zhongshan District and Da'an District, respectively. BCR has a negative correlation of 40% with residential prices in Zhongshan District, while it shows positive correlations of 16% and 7% for Shilin District and Da'an District, respectively. In terms of FYW and RYW, there is a positive correlation of 15% and 2% for Shilin District. However, for Zhongshan District, there is a negative correlation of 73% and 9%. In Da'an District, due to more consistent land use zoning, only the coefficient estimate for RYW is 0.031, indicating that an increase in RYW by one unit results in a positive impact of 3.1%. ER shows a positive correlation of 2% in Shilin District, and negative correlations of 36% and 10% in Zhongshan and Da'an Districts, respectively. Regarding the DISMRT, there is a negative correlation of 10% and 4% in Shilin and Zhongshan Districts, respectively, while in Da'an District, there is a positive correlation of 2.9%. Next, regarding macro-economic variables, AR, BGR and IR are negatively correlated with housing prices in Shilin District and Zhongshan District. In Da’an District, the AR is positively correlated with residential total prices by 0.9%. Lastly, regarding explanatory variable, FNM shows approximately a 1% to 1.2% positive correlation with housing prices across the three districts, and FD incident results in approximately a 0.07% to 2% negative correlation.

In the QR models, we use the 0.1, 0.25, 0.5, 0.75 and 0.9 quantile to represent residences in the three districts at low, lower-middle, middle, upper-middle, and high price levels respectively. In the estimated results, Pseudo R^2 ranges between 0.416 and 0.848. Area has the greatest impact on high-priced properties, which the impact diminishes as prices decrease. Age has the greatest impact on moderately high-priced in Zhongshan District, while its influence across different quantiles in Da'an District is relatively minor. For apartments, there is a negative impact of approximately 5% across all three districts, with the largest effect observed on moderately high-priced homes in Shilin District and the smallest on high-priced residences in Zhongshan District. Next are the FAR and BCR in the Resilient City Index. FAR shows a negative correlation across all quantiles in Shilin District, with the highest impact on middle to high-priced homes, whereas in Da'an District, it correlates positively across all quantiles, with a significant impact on low to mid-priced homes. BCR displays a positive correlation across all quantiles in Shilin District, particularly affecting the mid to low-priced homes. Conversely, it correlates negatively across all quantiles in Zhongshan District, affecting mid to low-priced and mid-priced homes the most. In FNM, there is a positive correlation across all quantiles in all three districts. It has a significant impact of approximately 0.6% to 2.3% on high-priced homes in Shilin District, middle to high-priced homes in Zhongshan District, and mid to low-priced homes in Da'an District. Regarding the FD, it results in a negative impact of 0.9% to 1.6% across all quantiles in Shilin District, except for low-priced homes, and a negative impact of 0.1% to 0.4% across all quantiles in Zhongshan District, except for low-priced homes. In Da'an District, apart from mid to low-priced homes, it shows a positive impact of 0.1% to 0.5% across all other quantiles.

Table 3 2SLS and two stage quantile regression (2SQR) estimates of the spatial lag model

	2SLS	0.1	0.25	0.5	0.75	0.9
			Shilin Dist.			
AREA	0.914 ***	0.673 ***	0.805 ***	0.952 ***	1.07 ***	1.167 ***
AGE	-0.034 ***	-0.036 ***	-0.028 ***	-0.039 ***	-0.05 ***	-0.033 ***
TYPE-B	0.031 ***	-0.006 ***	0.004 ***	0.033 ***	0.034 ***	0.021 ***
TYPE-A	-0.018 ***	-0.043 ***	-0.057 ***	-0.059 ***	-0.06 ***	-0.057 ***
FAR	-0.064 ***	-0.03 ***	-0.06 ***	-0.069 ***	-0.047 ***	-0.06 ***
BCR	0.104 ***	0.078 ***	0.14 ***	0.16 ***	0.14 ***	0.139 ***
FYW	0.128 ***	0.014 ***	0.134 ***	0.155 ***	0.156 ***	0.127 ***
RYW	0.014 **	0.002 ***	0.022 ***	0.011 ***	0.012 ***	0.01 ***
EXCAVATION	0.062 ***	-0.045 ***	0.03 ***	0.04 ***	0.047 ***	0.035 ***

	2SLS	0.1	0.25	0.5	0.75	0.9
AR	0.004 *	-0.023 ***	-0.004 ***	0.007 ***	0.011 ***	-0.003 ***
BGR	-0.008 ***	-0.014 ***	-0.006 ***	-0.001 ***	-0.0001 ***	-0.003 ***
IR	-0.005 *	-0.003 ***	0.001 ***	-0.001 ***	-0.006 ***	-0.003 ***
DISMRT	-0.07 ***	-0.097 ***	-0.109 ***	-0.091 ***	-0.069 ***	-0.053 ***
DISGREEN	-0.0005 *	-0.007 ***	-0.005 ***	-0.004 ***	0.005 ***	0.009 ***
FNM	0.011 ***	-0.003 ***	0.003 ***	0.01 ***	0.013 ***	0.014 ***
FD	-0.015 ***	-0.009 ***	-0.015 ***	-0.013 ***	-0.012 ***	-0.014 ***
Adjusted R^2	0.91	0.447	0.557	0.673	0.773	0.84
Zhongshang Dist.						
AREA	0.93 ***	0.753 ***	0.852 ***	0.951 ***	1.067 ***	1.177 ***
AGE	-0.058 ***	-0.069 ***	-0.062 ***	-0.063 ***	-0.059 ***	-0.048 ***
TYPE-B	0.025 ***	0.034 ***	0.028 ***	0.016 ***	0.014 ***	0.012 ***
TYPE-A	-0.002 *	-0.028 ***	-0.025 ***	-0.022 ***	-0.017 ***	-0.003 ***
FAR	0.017 ***	0.045 ***	0.036 ***	0.048 ***	0.003 ***	-0.025 ***
BCR	-0.325 ***	-0.391 ***	-0.489 ***	-0.436 ***	-0.191 ***	-0.034 ***
FYW	-0.622 ***	-0.618 ***	-0.823 ***	-0.716 ***	-0.341 ***	-0.137 ***
RYW	-0.074 ***	-0.075 ***	-0.113 ***	-0.094 ***	-0.037 ***	-0.002 ***
EXCAVATION	-0.342 ***	-0.28 ***	-0.381 ***	-0.344 ***	-0.164 ***	-0.091 ***
AR	0.002 *	0.002 ***	0.012 ***	0.011 ***	-0.006 ***	-0.016 ***
BGR	-0.009 ***	0.002 ***	-0.0006 ***	-0.003 ***	-0.01 ***	-0.013 ***
IR	-0.007 ***	-0.023 ***	-0.015 ***	-0.013 ***	-0.0007 ***	0.006 ***
DISMRT	-0.039 ***	-0.034 ***	-0.047 ***	-0.044 ***	-0.039 ***	-0.027 ***
DISGREEN	0.004 ***	0.005 ***	-0.0002 ***	0.001 ***	0.0006 ***	-0.0007 ***
FNM	0.015 ***	0.01 ***	0.011 ***	0.013 ***	0.016 ***	0.013 ***
FD	0.001 *	0.002 ***	0.0006 ***	-0.002 ***	-0.006 ***	-0.003 ***
Adjusted R^2	0.94	0.604	0.689	0.76	0.817	0.855
Da'an Dist.						
AREA	0.896 ***	0.858 ***	1.011 ***	1.123 ***	1.268 ***	1.39 ***
AGE	-0.05 ***	-0.011 ***	-0.029 ***	-0.037 ***	-0.044 ***	-0.043 ***
TYPE-B	0.071 ***	0.001 ***	-0.003 ***	0.004 ***	0.011 ***	0.005 ***
TYPE-A	-0.043 ***	-0.049 ***	-0.042 ***	-0.043 ***	-0.042 ***	-0.041 ***
FAR	-0.061 ***	0.018 ***	0.01 ***	0.018 ***	0.023 ***	0.018 ***
BCR	0.114 ***	0.106 ***	0.088 ***	0.03 ***	-0.008 ***	-0.019 ***
FYW	- -	0.12 ***	0.095 ***	0.04 ***	0.005 ***	-0.014 ***
RYW	0.006 *	0.039 ***	0.037 ***	0.023 ***	0.009 ***	-0.002 ***
EXCAVATION	-0.07 ***	- -	- -	- -	- -	- -
AR	-0.006 *	0.004 ***	0.017 ***	0.016 ***	0.003 ***	0.003 ***
BGR	-0.006 ***	0.0005 ***	0.001 ***	-0.001 ***	-0.007 ***	-0.006 ***
IR	-0.008 **	-0.002 ***	-0.004 ***	0.001 ***	0.01 ***	0.01 ***
DISMRT	0.047 ***	0.013 ***	0.005 ***	0.006 ***	0.004 ***	0.003 ***
DISGREEN	-0.029 ***	-0.0006 ***	0.0007 ***	0.001 ***	-0.001 ***	0.004 ***
FNM	0.005 *	0.018 ***	0.021 ***	0.014 ***	0.008 ***	0.007 ***
FD	-0.011 ***	0.004 ***	-0.005 ***	-0.002 ***	-0.0006 ***	0.001 ***
Adjusted R^2	0.9	0.534	0.616	0.697	0.774	0.841

Next, in the 2SLS result as shown in Table 3, the R^2 for the three districts are 0.91, 0.94, and 0.90 respectively. For Shilin District, besides area, significant variables influencing housing prices include BCR and FYW, with estimated coefficients of 0.104 and 0.128. This suggests that an increase in BCR and FYW by one unit would increase prices by 10.4% and 12.8% respectively. In Zhongshan District, resilience urban variables such as BCR, FYW, and ER each negatively impact residential prices by 32.5%, 62.2%, and 34.2% respectively. In Da'an District, the primary influencing variable is area, with an estimated coefficient of 0.896, significant at the 1% level. This indicates that an increase of one ping in area would increase housing prices by 89.6%. The secondary influencing variable is BCR, with an estimated coefficient of 0.114, indicating a 11.4% increase in housing prices with an increase of one unit in BCR.

In the SQR model, the estimated Pseudo R^2 ranges between 0.447 and 0.855. FNM has a negative impact of 0.3% on low-priced properties in Shilin District, while it shows positive correlations ranging from approximately 0.3% to 1.4% for other price ranges. In Zhongshan District, the impact is consistently positive across all quantiles, increasing by approximately 1% to 1.6% with each additional flood record. Similarly, in Da'an District, the impact is positive across all quantiles, increasing by approximately 0.7% to 2.1% with each additional flood record, particularly impacting medium to low-priced homes. Regarding the FD, in Shilin District, it results in a negative impact ranging from approximately 0.9% to 1.5%, with a greater impact on medium to low-priced homes. In Zhongshan District, it has a positive impact of 0.06% to 0.2% on low and medium-low-priced homes, but a negative impact of 0.2% to 0.6% on medium, medium-high, and high-priced homes. In Da'an District, it has a positive impact of 0.4% on low-priced properties, while it results in a negative impact ranging from 0.06% to 0.5% on other price ranges.

5. Conclusion

This study primarily investigates whether recent flood events in Taipei City's Shilin District, Zhongshan District, and Da'an District have impacted residential property prices over the past decade, and explores the speed and reasons for their recovery. The transaction samples from these three districts are divided into experimental and control groups to observe the potential impact of flood events on residential property prices. Therefore, a two-stage least squares method and spatial quantile regression are employed for analysis.

Firstly, among the individual residential property characteristics, the floor area positively influences housing prices, with larger residential areas commanding higher prices. The age of the building negatively affects housing prices, aligning with findings from Case & Shiller (1898), which suggest that time leads to depreciation and reduces market value of homes. Housing type, such as condominiums versus apartment buildings, also plays a role, with condominiums generally fetching higher prices, consistent with research by Yen (2019). In the districts of Shilin, Zhongshan, and Da'an, apartment buildings show a positive correlation, whereas apartments exhibit a negative correlation, possibly due to amenities such as elevators and management organizations in buildings, which enhance convenience and safety.

In the resilience city indicators, the FAR shows a negative correlation across all price ranges in Shilin District, whereas it is positively correlated in Zhongshan and Da'an Districts. The findings in Shilin District contrast with Wu Yiru's (2008) study on FAR, as plot ratio directly impacts building height, and Shilin

District has more diverse land use compared to the other two districts, with a higher proportion of residential types such as villas in the upper price ranges. BCR was initially expected to negatively correlate with housing prices, aligning with the findings in Zhongshan District but positively correlating with prices in Shilin and Da'an Districts. FYW and BYW show positive correlations in Shilin and Da'an Districts, consistent with the original expectations of this study, while in Zhongshan District, they exhibit a negative correlation. In terms of ER, it shows a negative correlation with low-priced housing in Shilin District and all quantiles of housing in Zhongshan District. However, in the QR models and SQR in Daan District, ER is not representative due to Daan District's zoning regulations for residential areas (Residential Zone III and IV) and commercial areas (Commercial Zone III and IV), which have a standardized excavation rate of 0.8 under the Land Use Control Autonomy Ordinance. Traditional neighborhood environmental variables are included as resilience urban indicators in the study. DISMRT represents transportation accessibility, while DISGR not only indicates residents' recreational capabilities but also mitigates disaster impacts during floods, enhancing urban drainage. The variable of distance to metro stations shows negative correlations across all three districts, consistent with Forrest et al. (1996), suggesting noise issues near metro stations. Li et al. (2017) also indicated that residential prices within 300-500 meters from metro stations are higher compared to those within 0-300 meters. Lastly, regarding the variable of distance to green spaces, it shows positive correlations with high-priced housing in all three districts. When the distance to green spaces increases by one meter, the total housing price increases by approximately 0.1%. However, in terms of overall variables, the impact of distance to green spaces on total price is relatively small.

Finally, regarding the external variables of interference, this study selected the number of times the transaction samples were flooded before the transaction. Bin et al. (2008) indicated that people typically consider previous flood events before purchasing property. In the study results, whether using quantile regression or spatial quantile regression, except for low-priced properties in Shilin District, properties of different price ranges in the other districts show a positive correlation. This suggests that for each additional flood occurrence, the total price in the three districts increases by approximately 1.5%. Possible reasons include the gradual forgetting of flood risks over time, as noted by Rajapaksa et al. (2017), or as described by Tobin & Montz (1994), most properties retain their value even after flooding and may even appreciate due to completed repair works. Additionally, the impact of flood depth on total housing prices is generally negative, consistent with the expected results.

Ministry of the Interior and the Taipei City Hydraulic Engineering Office have respectively disclosed the Real Price Registration System and the Taipei City Flood Information Network based on principles of information transparency. The goal is to allow the public to reference multiple sources of information before purchasing properties and to enhance market transparency to address information asymmetry issues. According to the 2015 Ministry of the Interior Housing Market Trends Survey Report, 79.6% of the population checks the transaction prices in the real price registration system before buying a house. However, according to the results of this study, the impact of pre-transaction flood frequency and flood depth on residential total prices is relatively minor. This could be because even with past flooding experiences, compared to the losses from flooding events studied in previous literature, the impact is less significant and fades relatively quickly. Variables related to land use regulations have a relatively significant impact in the Zhongshan District, possibly due to the large-scale residential planning in areas like Dazhi, which mainly consist of new residential buildings subject to land use regulations.

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