Is it the Flood, or the Disclosure? An Inquiry to the Impact of Flood Risk on Residential Housing Prices

Abstract

In 2015, the government of Taipei, Taiwan, published a series of flood risk maps based on simulation results. It sparked a broad public debate on flood risk information and the real estate market. This study therefore investigates the effect of making flood risk information public on residential housing prices and makes the following contributions. The first contribution concerns public policy. By analysing the relationship between the published flood risk information and more than 12,000 central Taipei sales records in 2015 and 2016, this study finds that the effect of flood risk on housing prices is significant and negative both before and after the maps were disclosed. Although some local variation in the effect of flood risk after the map disclosure was identified, there is no evidence that the disclosure altered the effect on housing prices. This finding suggests that the disclosure of the flood risk maps impacted the effect of the flood risk locally without influencing the market as a whole. Another contribution concerns perception. The result indicates that homebuyers' negative attitude towards flood risk mainly focuses on the risk under low-intensity, high-frequency rainfall conditions. The final contribution of this study concerns its methodological perspective. By combining the spatial fixed-effect (SFE) model with geographically weighted regressions (GWRs), this study successfully mitigates the endogeneity problem while addressing the heterogeneity problem.

Keywords: flood risk, hedonic price analysis, endogeneity, heterogeneity, geographically-weighted regression with spatial fixed-effect

1. Introduction

In September 2015, the Taipei city government published a series of flood potential maps, which illustrated simulated flood risk areas under extreme precipitation conditions. The disclosure of the maps sparked a broad public debate on flood risk information and the real estate market. On the one hand, supporters of the disclosure claim that flood risk information is essential to inform real estate transactions, and it is the government's responsibility to provide trustworthy information. It is especially essential since flooding has long been a critical natural hazard in Taipei. And it is generally agreed that the risk will only exaggerate in the context of global warming.

Opponents of disclosing flood potential argue that it is arbitrary to publicly assign flood risky areas based only on simulations and that disclosure constitutes unnecessary interference in the real estate market. Residential property values are relatively high in Taipei. The average sales price of a residential unit is over $577,000 USD, while the median annual income per capita is only $43,000 USD. Given that they spend, on average, over 13 times their annual income on a house, home buyers are advised to be extremely careful in collecting the necessary information, including on flood risk, to support their decision to buy. Given that people were already doing their own research on flood potential even before the disclosure of the maps, theoretically, flood risk is being spontaneously internalized into sales prices. Therefore, it does not make a difference whether the government discloses flood risk information or not. Moreover, the information is not based on real events, but rather on simulations that take into account the capacity of the drainage system under different hypothetical precipitation rates. Thus, opponents argue that the disclosure only creates unnecessary disturbance to the housing market, if any.

This study aims to provide empirical evidence in the context of the debate on releasing flood risk maps. A hedonic price analysis with comprehensive spatial models is applied to identify the impact of flood risk on residential housing prices. Based on over 22,000 actual sales records spanning 2015 to 2016 in Taipei, this study compares the impact of flood risk before and after the disclosure of the government maps. If the effect of the flood impact on housing prices changes after the disclosure, both sides of the debate are supported. Supporters of the disclosure find evidence of information asymmetry before the disclosure, while opponents argue that the disclosure interferes with the market. However, the results of this study show that the negative impact of flood risk on housing prices was not significantly different before and after the map disclosure. Further investigation shows that the spatial distribution of the impact changed after the map disclosure. This finding implies that the map disclosure did not affect the market as a whole, but it did change the local awareness of flood risk in certain areas.

Another contribution of this study is its methodological perspective. Classic hedonic price analysis with ordinary least square (OLS) regression suffers from two spatial problems: the endogeneity problem caused by omitted spatial variables, and the heterogeneity concern when regression coefficients are presumed to be spatially constant (Bitter et al., 2007). Previous studies demonstrate sufficient solutions to these problems separately. However, endogeneity and heterogeneity have not been considered in a single model before. This study addresses the endogeneity and heterogeneity problems together by combining the spatial fixed-effect (SFE) model with geographically weighted regression (GWR). A section of the literature indicates that the hedonic price of certain environmental assets varies spatially by applying GWR. Since the endogeneity problem is usually not considered in typical GWR models, we argue that the omitted spatial-related variables bias the result of the GWR models. By combining the SFE model with GWR, this study concludes that the effect of flood risk maps is highly sensitive to a specific location, even after controlling for the spatial autocorrelation.

The main policy application of this result is to justify the act of publicly disclosing controversial data, such as flood potential information. Additionally, the fact that the impact of flood risk mapping on housing prices is spatially heterogeneous implies that the potential benefits of flood prevention policies should not be assessed simply by multiplying the hedonic price of flood risk by the number of houses. In other words, the effects of flood risk mapping vary dramatically by location.

2. Literature Review

The price of risk plays an important role in research related to the perception of flood risk in the urban environment (Berndtsson et al., 2019; de Koning et al., 2017; Hellman et al., 2018). Numerous studies focus on flooding by examining flood insurance in the context of climate change (Aerts & Botzen, 2011; Atreya et al., 2015; Botzen et al., 2009; Glenk & Fischer, 2010; Treby et al., 2006). But these studies are less applicable in the case of Taiwan, since flood insurance here is extremely unpopular compared to other countries. A relatively small body of research focuses on the impact of flooding and flood risk on property values (Harrison et al., 2001; Ismail et al., 2016; Sander & Haight, 2012; Tobin & Montz, 1988; Votsis & Perrels, 2015). Results of several meta analyses confirm the negative impact of flood risk on housing prices (Beltrán et al., 2018; Daniel et al., 2009). Beltran et al. (2018) indicates that for inland flooding, the price discount associated with location in the 100-year floodplain is 4.6 percent.

The policy interference, such as information disclosing, is sometimes critical to the price of risk (Hibiki & Managi, 2011). In the case of flood risk, Pope (2008) indicates that housing prices are affected not only by the flooding, but also by the disclosure of flood risk information. By comparing the effect of housing being located in a disclosed flood zone (required legislatively) compared to this information not being disclosed, a 4% decline in housing prices is associated with the disclosure. However, this study is conducted using OLS regression, which falls short in dealing with spatial issues (Bitter et al., 2007). Typical spatial concerns, such as endogeneity and heterogeneity, call into question the validity of the results obtained using OLS regressions.

Several spatial econometric methods have been developed or applied to mitigate endogeneity and heterogeneity concerns. For the endogeneity problem, i.e. the spatial autocorrelation issue, methods such as weighted repeated sales (Case & Shiller, 1989), instrumental variable (Irwin, 2002), the stochastic approach (Tse, 2002), the moving window approach (Páez et al., 2008), the spatial autoregressive model (Bin et al., 2008; Noonan et al., 2013; Samarasinghe & Sharp, 2010), spatial quantile regression (Rajapaksa, Wilson, et al., 2017) and SFE models (Anderson & West, 2006; Cavailhès et al., 2009) have been reported to be effective. In terms of application to flood-related issues, Cavailhès et al. (2009) applied an SFE model to determine the hedonic prices of landscapes, but found no significant effect of flood risk on housing prices. Notably, none of the models mentioned simultaneously deal with the concern of heterogeneity. This study applies the SFE model to address the endogeneity problem because it can be further integrated into GWR, which is designed to mitigate the heterogeneity problem.

Previous literature on the heterogeneity problem is relatively scarce. The spatial expansion method (Casetti, 1972), spatial error model (Hellman et al., 2018), unconditional quantile regression(Fernandez & Bucaram, 2019) and GWR (Bitter et al., 2007) have been reported to be effective in addressing the heterogeneity issue. GWR is selected in this study due to its compatibility with methods addressing endogeneity. In terms of applying GWR to water-related issues, Cho et al. (2006) estimated the hedonic price of proximity to water bodies using both the OLS model and the locally weighted regression model. The locally weighted model was reported to capture the spatial variability of willingness to pay for access to bodies of water.

From a methodology perspective, this study contributes to the literature by developing an advanced spatial econometric model that simultaneously addresses the endogeneity and heterogeneity problems. From a policy perspective, this study determines the hedonic price of flood risk taking into account spatial variations. Further, this study clarifies the distinction between the effect of flood risk and the effect of publicly disclosing that information, which could be useful when developing future flood-related policies.

3. Data and Methodology

3.1 Data

Data used in this study comes mostly from two sources. First, the flood risk maps published by the Taipei city government in September 2015 were used to represent flood risk in the city. The maps are a result of a comprehensive simulation based on the capacity of drainage systems and various precipitation intensity levels. The maps illustrate simulated flood areas in conditions where there is precipitation of 78.8 mm, 100 mm and 130 mm per hour (see the right side of Figure 1). The precipitation level of 78.8 mm in an hour is the rainfall intensity received once every five years in Taipei, and it is the reference level for the design of local drainage systems. In other words, if the drainage system works as designed, no flooding should occur at this level of precipitation intensity. The 100 and 130 mm per hour scenarios are both situations where the precipitation exceeds drainage capacity and flooding would be inevitable by design. Note that only urban downpour flooding is considered here. River and sea flooding is unlikely to occur under the given precipitation level.

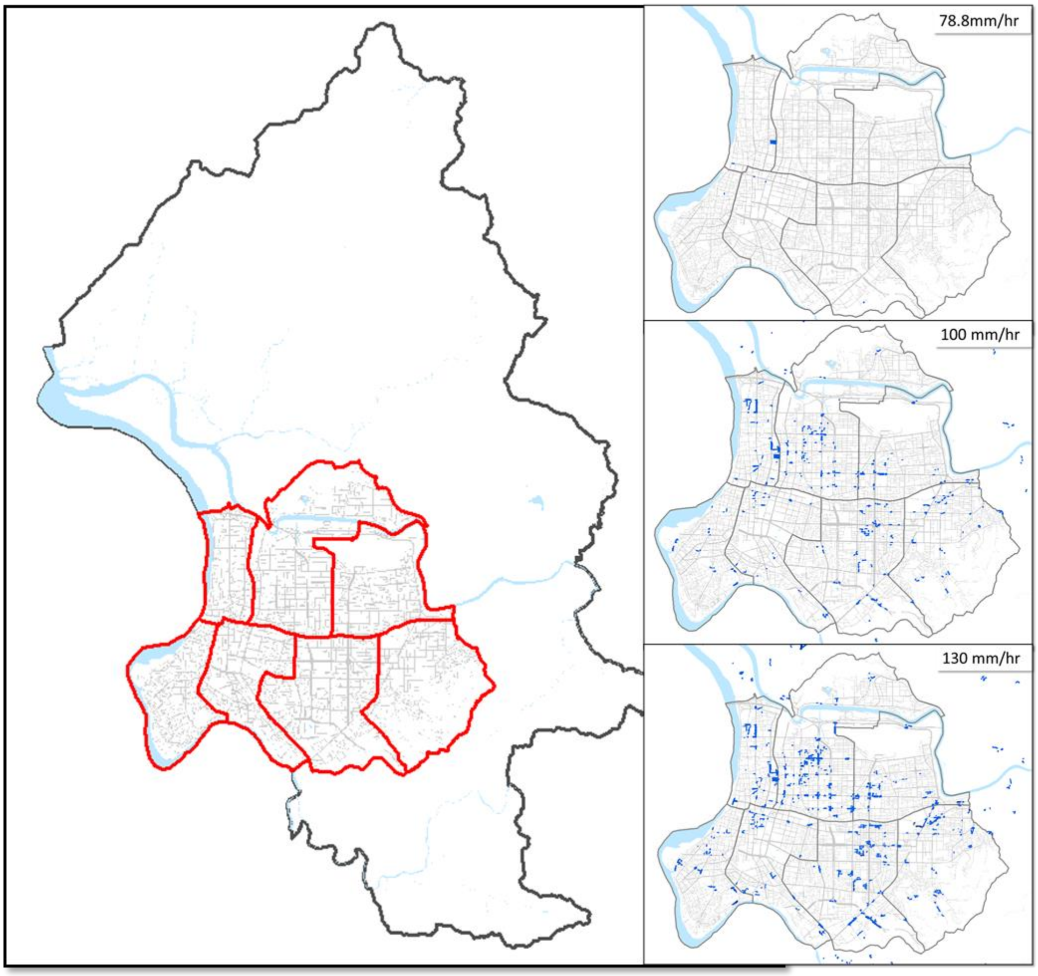

Figure 1. Taipei maps of flood risk under various precipitation conditions.

The residential property sales data used in this study was collected from the Department of Land Administration’s (DLA) actual sales price registration system. We included 12,266 sales records from 2015 and 2016 for properties located in seven central districts of Taipei (see the left side of Figure 1). Taipei is a basin surrounded by mountains. Four surrounding districts were excluded from the study for two reasons. First, mountainous areas with low housing density in these four districts create potential outliers when analysing data based on spatial distribution. Second, home buyers’ tolerance of flood risk may be different for urban and rural houses.

Focusing on urban areas allows us to determine the hedonic price of flood risk in an urban environment.

For each sales record, we recorded basic property characteristics including square footage, age of building when the transaction occurred, building type (condominium/mansion), number of rooms and bathrooms, whether there is a management committee and the number of parking spaces. To identify the effect of the floor or level a property is located on, a categorical variable named *floor level* was created based on the relative vertical location of the property. For example, the relative height of a third floor property in a four floor condominium is 0.75; thus, the *floor level* is 3 (between 0.6 to 0.8). Neighbourhood characteristics, such as accessibility to the nearest subway (MRT) station and park, were captured using ArcGIS.

Data from two sources were integrated using an ArcGIS scheme. For each sales record, the distance to the nearest flood potential area was calculated. Note that the flood maps only illustrate flood area on public land use, mainly on the roads. Thusm commonly used dummy flood variable, such as inside/outside the flood zone (Netusil et al., 2019; Rajapaksa, Zhu, et al., 2017), is not suitable in this case. In this study, the *flood* variable is defined as the inverse of distance to the nearest flood area. The hypothesis here is that the effect of flood on housing prices decays rapidly as distance increases. Due to the variable design, this study discusses homebuyers' attitudes towards nearby flood risk, rather than the willingness to pay to avoid flood in the house. Table 1 lists the descriptive statistics of the variables included in the model.

Table 1. Descriptive statistics of variables.

	Obs.	Mean	Std. Dev.	Min	Max

Sale price (logged)	12,266	16.7	0.8	13.1	24.0
Flood dist. (78.8 mm, 1/m)	12,261	0.001	0.004	0.0002	0.18
Flood dist. (100 mm, 1/m)	12,188	0.016	0.216	0.0009	17
Flood dist. (130 mm, 1/m)	12,138	0.032	0.788	0.0009	71
Area (m^2)	12,266	123.59	632.87	7.16	69,126
Age (yr)	12,266	17.65	15.63	0.00	97
Floor level (0 to 5)	12,266	3.45	1.28	1	5
Condo (≤5 storeys)	12,266	0.22	0.42	0	1
Condo (6~10 storeys)	12,266	0.35	0.48	0	1
Mansion (>10 storeys)	12,266	0.20	0.40	0	1
Rooms	12,266	2.21	1.34	0	10
Bathrooms	12,266	1.45	0.83	0	10
Management committee	12,266	0.62	0.48	0	1
Parking	12,266	0.36	0.72	0	6
Dist. to MRT Stn. (1/m)	12,266	0.004	0.006	0.0005	0.28
Dist. to park (1/m)	12,099	0.022	0.268	0.0019	17.40
Sales in 2016	12,266	0.394	0.489	0	1

3.2 Methodology

This study develops an advanced spatial econometric model that combines the SFE model and the GWR method. The analysis consisted of two stages. In the first stage, the SFE model was used to control for endogeneity. Consider an OLS model that focuses on the hedonic price of flood risk:

$$\ln(sales\,price) = \beta_0 + \beta_1(flood\ \ risk)\ \ + \beta_2 X\ \ +\ (\gamma q + \nu),$$

where the dependent variable is logged sales price and the variable of interest is the flood risk to a certain property. All the other independent variables, including property characteristics (age, area, etc.) and neighbourhood characteristics (access to park, MRT, etc.), are listed in the matrix X. β_0 to β_2 denote the coefficient matrices for each variable category, q represents the omitted variable, γ denotes the coefficient of q, and ν is the actual residual. The issue of endogeneity arises when

q is spatially correlated with flood risk, which is likely to occur in most cases. For example, the level of flood risk relates directly to the quality of the local drainage system. The quality of the local drainage system is, in turn, correlated with the quality of other infrastructure, and so it can reasonably be used as an explanatory variable for property values. When the quality of other infrastructure is omitted from the model (because there is no proper measure for it), endogeneity occurs, which biases the coefficient for flood risk in the OLS regression.

The SFE model can be used to mitigate this problem and can be illustrated as follows:

$$\left[\ln(sp)_{ij} - \overline{\ln(sp)_j}\right] = \left[(flood)_{ij} - \overline{(flood)_j}\right]\beta_1 + \left(X_{ij} - \overline{X_j}\right)\beta_2 + \left(\gamma_j q - \overline{\gamma_j q}\right) + \left(v_{ij} - \overline{v_{ij}}\right),$$

where the subscript *i* denotes each sales record, and the subscript *j* represents the spatial district in which *i* is located. For each observation *i*, the mean of each variable within the spatial district *j* is subtracted. Assuming that the omitted variable q is uniformly distributed in spatial district *j*, i.e. $\gamma_j q$ is identical to $\overline{\gamma_j q}$, the omitted variable is removed from the model, which reduces the endogeneity problem. In this study, the spatial district *j* refers to village jurisdictions. There are 260 villages in the research area. Other spatial districts, such as the second dissemination area[1], were also considered. The results from using villages and the second dissemination area share the same trends. Villages were selected as the level for spatial analysis because they are governmental jurisdictions and it is reasonable to argue that the omitted variable of infrastructure quality relates to governmental jurisdictions.

[1] The second dissemination area is the statistical area published by the Ministry of the Interior (MOI), Taiwan. The areas are divided based on demographic conditions of the residents. There are 497 districts in the study area.

In the second stage, the difference-to-local-means data that was created to run the SFE model was applied to the GWR model. The idea of GWR is that by conducting multiple local regressions for each observation, the spatial fluctuations within the magnitude of the effect of flood risk can be illustrated. The number of neighbours included in each local regression is determined by the selection of kernel type and bandwidth method. The kernel type is set as fixed in this study, since the density of sales records in central Taipei is relatively constant. The bandwidth is set as the Akaike Information Criterion (AICc), which refers to the fact that the extent each local regression is determined using the AICc.

Previous studies using GWR show that heterogeneity exists (Bitter et al., 2007; Cho et al., 2008). However, as typical GWR only allows local regressions under OLS, the endogeneity issue arises when dealing with heterogeneity. By applying difference-to-local-means data created using the SFE model, this study aims to illustrate the spatial distribution of the effects of flood risk on housing prices, while simultaneously considering the problem of endogeneity.

4. Results and Discussion

4.1 The SFE Model

This study aims to determine the effect of flood risk on residential housing price. As mentioned previously, the flood risk maps disclosed by the Taipei government are used to represent flood risk. We determined the hedonic price of flood risk under 78.8 mm/hr, 100 mm/hr and 130 mm/hr precipitation rates. First, this study compared the results between the OLS and SFE models (Table 2 lists these results). The results for other control variables are not included for simplicity. To determine whether the influence of flood risk changed after the map disclosure, observations were divided into *before* and *after* groups for both the OLS and SFE models. The maps were disclosed in September 2015. Thus, any transaction registered after October 2015 was considered part of the *after* group.

Table 2. Flood effect results for the OLS and SFE models.

	OLS		SFE (village)	
	Before	**After**	**Before**	**After**
Dist. to flood (78.8 mm/hr)	-12.153 **	-15.783 ***	-3.847 ***	-4.913 **
	(5.0524)	(4.8678)	(.9077)	(2.1452)
Dist. to flood (100 mm/hr)	-0.022 *	0.027	-0.018	0.021
	(.0134)	(.0192)	(.0142)	(.0150)
Dist. to flood (130 mm/hr)	-0.001	-0.002	0.003	-0.007 ***
	(.0049)	(.0013)	(.0051)	(.0017)

*p < .10, **p < .05, ***p < .01

The OLS and SFE model results generally share the same pattern. For flood risk at the precipitation intensity of 78.8 mm/hr, the effect of flood risk on housing prices was negative and significant for both *before* and *after* groups. For flood risk at stronger rainfall intensities, using the SFE model, the effect on housing prices is only significant for the *after* group and its magnitude is trivial. Holding all the other variables constant, the sales price of a property with a flood area 10 meters away is only 0.07% lower than that of a property with a flood area 100 meters away. This result implies that home buyers worry more about flood risk under low-intensity, high-frequency rainfall conditions rather than high-intensity, low-frequency conditions. Note that 78.8 mm/hr is the minimum reference precipitation rate for the local drainage system. In this sense, home buyers care more about the risk of a flood that should not occur by design, than the risk of a flood caused by extreme precipitation events beyond the capacity of the city drainage system. Since the effect of flood risk only matters for rainfall intensity levels of 78.8 mm/hr, the remainder of this section focuses on the effects of flood risk at 78.8 mm/hr precipitation intensity.

The purpose of the comparison between the OLS and SFE models is to check whether endogeneity is an issue for OLS. If it is, then the question becomes whether the SFE model mitigates the problem. The Global Moran's Index (Moran's I) is used for both purposes. Moran's I measures spatial autocorrelation, which can be understood as the relationship between the distance and similarity of certain characteristics. The index ranges from 1 to -1, where 1 indicates that 'values cluster together' and -1 indicates that 'dissimilar values are next to each other'. The severity of endogeneity is identified by checking the Moran's I of standardized residuals for OLS regressions. Further, by comparing the Moran's I of standardized residuals between OLS and SFE models, the effect of SFE is illustrated (see Table 3). For OLS, the Moran's I of residuals for both the *before* and *after* groups is over 0.3, which shows significant clustering. For SFE, the Moran's I drops significantly. The values much closer to zero indicate that SFE controls the endogeneity problem to a certain extent. It is evident that SFE is the preferred model considering endogeneity. Thus, further interpretation will focus solely on the SFE model results.

Table 3. Global Moran's I for standardized residual for OLS and SFE results.

		OLS	**SFE**
Before	**Moran's I**	**0.327** ***	**0.080** ***
	(z-score)	(52.60)	(12.86)
After	**Moran's I**	**0.300** ***	**0.110** ***
	(z-score)	(64.99)	(23.90)

*p < .10, **p < .05, ***p < .01

To further investigate the effect of the disclosure, Table 4 lists the full SFE results for flood potential at the precipitation level of 78.8 mm/hr. While the effects of flood risk remained negative and significant after the disclosure, coefficients for other variables fluctuated. One possible explanation for the fluctuation is a serious recession in the real estate market that took place in 2016 due to a series of property tax adjustments. From 2015 to 2016, sales records dropped by 36% and the average sales price dropped by nearly 28%. It is not surprising that home buyers' preferences are blurred by an unstable market. However, the effects of flood risk remained relatively stable after controlling for other property and neighbourhood characteristics. Controlling for all the other variables, before the disclosure, the sales price of a property with flood area located 100 meters away is 3.847% lower than that of a property with a flood area located 1,000 meters away. This negative effect increased after the disclosure. The differences in the effect of flood risk information between the *before* and *after* groups was tested by adding interaction terms between all variables and *after* in the pooled model. Generally, coefficients of non-interacting variables should be similar to the result of the *before* group, and the significance of the interacting terms will show whether the results for the two groups are significantly different. The result for the *flood*after* variable shows that the effect of flood risk information on real estate prices is not significantly different after the disclosure.

Table 4. SFE results for flood potential at the precipitation level of 78.8 mm/hr.

	Before	After	Interaction
Number of obs.	5,127	6,967	12,094
Number of groups	260	260	260

Overall R-square	0.7358	0.5231	0.6162
Flood variable (78.8mm)	**-3.847 *****	**-4.913 ****	**-4.733 *****
Area (m^2)	0.005 ***	0.0001 ***	0.0046 ***
Age	-0.005 ***	-0.006 ***	-0.0056 ***
Floor level	0.058	-0.100 ***	-0.0675 *
Floor level sq.	-0.011 **	0.011 **	0.0065
Condo (≤5 storeys)	0.149 ***	0.154 ***	0.1235 ***
Condo (6~10 storeys)	0.386 ***	0.508 ***	0.3771 ***
Mansion (>10 storeys)	0.340 ***	0.381 ***	0.3167 ***
Rooms	0.063 ***	0.097 ***	0.0649 ***
Bathrooms	0.043 ***	0.126 ***	0.0390 **
Management committee	-0.055 **	-0.129 ***	-0.0929 ***
Parking	0.022	0.384 ***	0.0335
Dist. to MRT Stn. (1/m)	2.278 **	0.795	2.1333 **
Dist. to park (1/m)	-0.013 ***	0.004	-0.0155 ***
Sales in 2016		-0.066 ***	
Flood*after			0.4512
Area*after			-0.0044 ***
Age*after			0.0002
Floor level*after			0.0519 *
Floor level sq.*after			-0.0074
Condo≤5*after			0.0531
Condo6-10*after			0.1501 ***
Mansion*after			0.0866 *
Rooms*after			0.0335 **
Bathrooms*after			0.0920 ***
Mgmt. comm.*after			-0.0139
Parking*after			0.3538 ***
MRT*after			-1.4170
Park*after			0.0345
Constant	15.804 ***	16.268 ***	16.060 ***

*p < .10, **p < .05, ***p < .01

4.2 GWR with SFE Models

To test whether the heterogeneity issue exists even after controlling for the endogeneity problem, this study applied the data prepared for the SFE model to the GWR model. Since previous tests showed that the influence of flood potential is only statistically significant for precipitation level of 78.8 mm/hr, the following discussion focuses on 78.8 mm/hr. Again, observations are divided into *before* and *after* groups to determine the effect of the flood risk information disclosure. Figures 2 and 3 illustrate the results of local regressions that controlled for spatial autocorrelation, and Tables 5 and 6 list some comparisons between the global SFE model and the local regression (SFE-GWR) results.

Figures 2 and 3 show a clear spatial variation of the effects of flood risk information in both the *before* and *after* groups. The magnitude of the effect is divided into six groups following Jenks natural breaks optimization method. Observations showing a strong negative effect are shown as green, while strong positive effects are shown as red. Observations with relatively mild effects are shown with colours ranging between green and red. Before the disclosure of the maps, the effects of flood risk on housing prices was generally negative, which is consistent with the SFE results. Areas showing positive attitudes toward flood potential share two common characteristics: they have no flood potential areas in nearby neighbourhoods and the nearest flood potential areas and the ‘centres’ of the city are generally in the same direction. Thus, one possible explanation for flood risk information having a positive effect on housing prices is that the effect is capturing the spillover for distance to city centres, which is omitted in this study. The centre effect is difficult to control for because the business, commercial and transportation centres are decentralized in Taipei, and their precise location changes over time. Further investigation is required to clarify the centre effect.

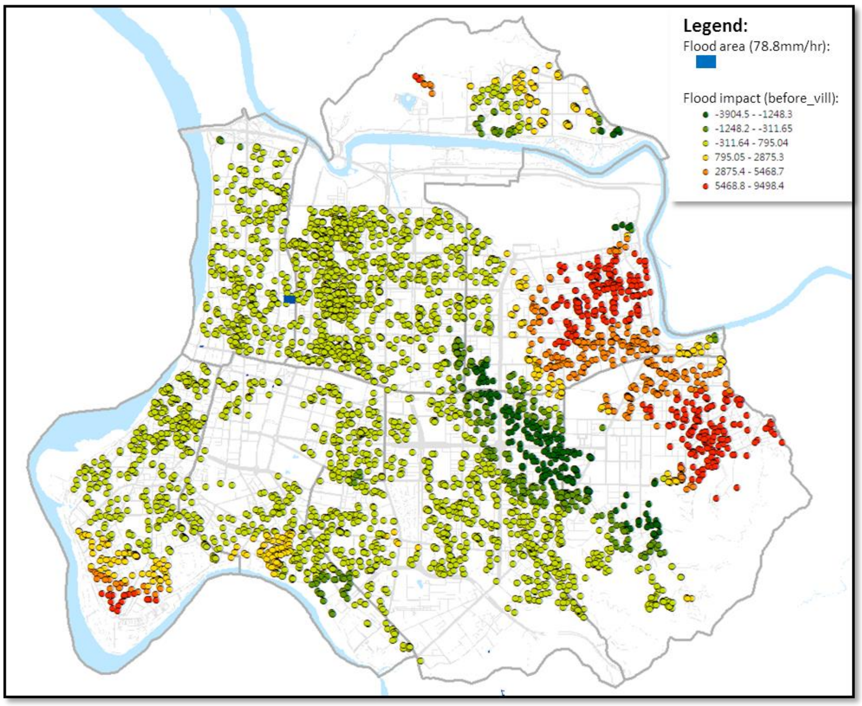

Figure 2. Results of GWR with SFE for *before* group.

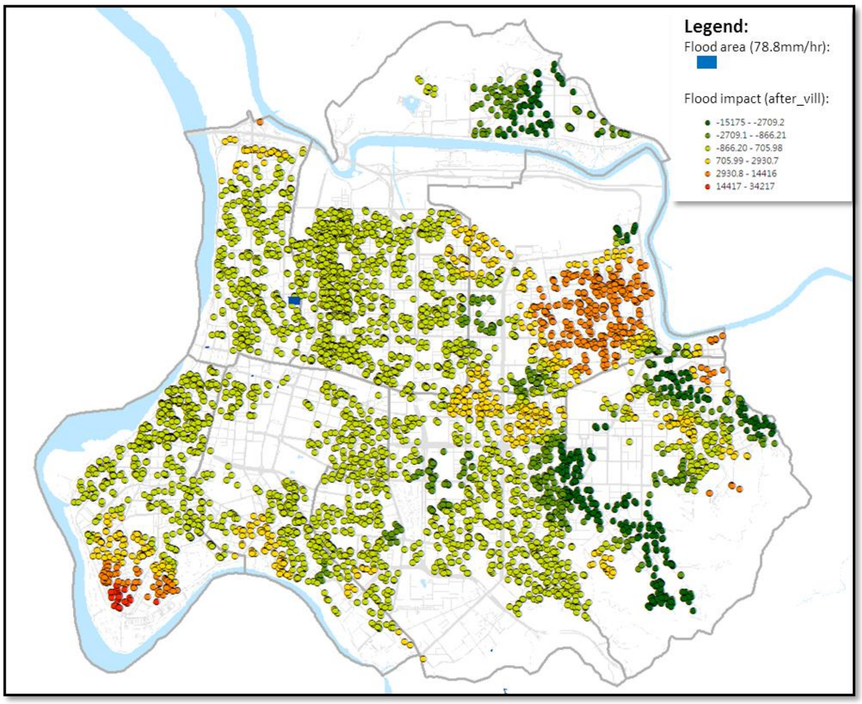

Figure 3. Results of GWR with SFE for *after* group.

Comparing Figures 2 and 3, the effect of flood risk on housing prices remains mildly negative (represented by light green) in most areas even after the disclosure.

However, some local changes were observed after the disclosure of the maps. For example, the strong positive effect in Songshan and Xinyi districts (on the right of Figure 2) and the strong negative effect in the north east of Da-an district (in the middle of Figure 2) were both significantly reduced after the disclosure. These changes indicate that the disclosure of flood risk maps influences home buyers' attitudes toward flood potential on a local level, even though the difference is not statistically significant globally.

As mentioned above, GWR performs a local regression for each observation to describe the spatial distribution of regression coefficients. Tables 5 and 6 show the distribution of these coefficients. As expected, coefficients for spatial variables, such as the flooding variable (which is inverse to the distance to the nearest flood potential area) and distance to the nearest MRT station, generally show greater variety than property characteristic coefficients. A local regression only contains observations in a relatively small area. Thus, spatial effects are further amplified in a small area, as the difference in distance between observations could be tiny.

Table 5. Comparison of SFE and SFE-GWR results for the *before* group.

	Global SFE	**SFE-GWR**				
Number of obs.	5,127	5,127				
Overall R-square	0.7358	0.801				
		Min.	**Q1**	**Median**	**Q3**	**Max.**
Flood variable (78.8mm)	**-3.847 *****	**-3904.5**	**-4.276**	**7.259**	**867.3**	**9498.4**
Property characteristics						
Area (m^2)	0.005 ***	0.002	0.005	0.006	0.007	0.018
Age	-0.005 ***	-0.041	-0.009	-0.003	-0.001	0.003
Floor level	0.058	-0.662	-0.083	0.002	0.130	0.400
Floor level sq.	-0.011 **	-0.062	-0.019	-0.004	0.010	0.096
Condo (≤5 storeys)	0.149 ***	-0.413	0.066	0.160	0.237	0.974
Condo (6-10 storeys)	0.386 ***	-0.521	0.240	0.324	0.435	0.699

Mansion (>10 storeys)	0.340 ***	-0.255	0.244	0.314	0.408	0.815
Rooms	0.063 ***	-0.143	0.014	0.049	0.078	0.156
Bathrooms	0.043 ***	-0.224	-0.011	0.028	0.088	0.236
Management committee	-0.055 **	-0.411	-0.084	-0.025	0.041	0.220
Parking	0.022	-0.796	-0.148	-0.068	0.002	0.327
Spatial variables						
Dist. to MRT Stn. (1/m)	2.278 **	-1073.036	-1.554	1.594	6.321	150.038
Dist. to park (1/m)	-0.013 ***	-2.339	-0.030	0.010	0.292	3.035

*p < .10, **p < .05, ***p < .01

Table 6. Comparison of SFE and SFE-GWR results for the *after* group.

	Global SFE	**SFE-GWR**				
Number of obs.	6,967	6,967				
Overall R-square	0.5231	0.777				
		Min.	**Q1**	**Median**	**Q3**	**Max.**
Flood variable (78.8mm)	**-4.913 *** **	**-15175.4**	**-89.089**	**1.819**	**295.4**	**34217.2**
Property characteristics						
Area (m^2)	0.0001 ***	0.000	0.002	0.005	0.007	0.012
Age	-0.006 ***	-0.062	-0.012	-0.005	-0.002	0.006
Floor level	-0.100	-0.573	-0.090	-0.024	0.086	0.518
Floor level sq.	0.011 **	-0.075	-0.013	0.003	0.011	0.082
Condo (≤5 storeys)	0.154 ***	-0.631	-0.035	0.112	0.300	2.816
Condo (6-10 storeys)	0.508 ***	-0.357	0.237	0.342	0.435	0.964
Mansion (>10 storeys)	0.381 ***	-0.463	0.199	0.288	0.376	0.756
Rooms	0.097 ***	-0.114	0.046	0.075	0.099	0.323
Bathrooms	0.126 ***	-0.250	-0.035	0.033	0.118	0.388
Management committee	-0.129 **	-0.379	-0.125	-0.041	0.027	0.776
Parking	0.384	-0.525	-0.108	-0.008	0.153	0.637
Spatial variables						
Dist. to MRT Stn. (1/m)	0.795 **	-12607.9	-1.992	2.301	6.215	149.4
Dist. to park (1/m)	0.004 ***	-22.27	-0.565	0.038	0.513	4.852
Temporal variables						
Sales in 2016	-0.066 ***	-0.227	-0.058	-0.024	0.014	0.191

*p < .10, **p < .05, ***p < .01

Another advantage of performing GWR with SFE pre-treated data is that technical limitations are loosened. The issue of multicollinearity in a regression model arises when independent variables correlate with each other; it is especially an issue when the sample size is small and variation between variables is limited. Thus, multicollinearity is a critical concern when including dummy variables in GWR, since GWR involves a series of local regressions with a limited number of observations, and dummy variables lack variation by design. The SFE pre-treated data provides variation within variables by comparing each value with its local mean, thus sequentially counteracting the limitations of including dummy variables in GWR.

5. Discussion & Conclusion

This study reveals the influence of disclosing flood risk information on residential housing prices. The SFE results suggest that the effect of flood risk on housing prices is negative and significant even before it is publicly disclosed, and this effect does not significantly change after the governmental disclosure. In other words, there is no evidence that the disclosure of flood risk information creates 'unnecessary interference to the residential real estate market', as opponents of disclosure argue. On the other hand, the SFE-GWR results identify some local variations in the effect of disclosing flood risk, which implies that the disclosure of flood risk information has an effect on the attitudes of some homebuyers at the local level. Overall, the results of this study suggest that disclosure alters local awareness of flood risk without interfering in the residential real estate market. Thus, this study supports policies that would publish information with negative associations.

This study also investigated the effect of flood risk on housing prices, i.e., home buyers' attitude toward flood risk. The SFE results indicate that precipitation conditions dominate home buyers' attitudes toward flood risk. When precipitation intensity is low, the negative effects of flood risk on housing prices is significant. But as precipitation intensity increases, the effect fades away. There are several possible explanations for this. First, it could be the frequency of flooding events that home buyers really care about. In hydrology, intensity and frequency of precipitation are inversely proportional, which means that the negative effect of flood risk at low precipitation intensity could be perceived as an aversion to high frequency flood risk. Thus, the results could be indicating that home buyers care more about suffering from a mild flood every five years than the possibility of suffering from a severe flood that only occurs once in several decades. Also, evidence shows that the impact of flood on property value decays over time (Rajapaksa, Zhu, et al., 2017; Sado-Inamura & Fukushi, 2019). It has been over a decade since the last serious flood occurred in Taipei in 2003. The impact of severe flood might be underestimated overtime, thus only the impact of mild flood (which still occurs) was identified. The negative effect of flood risk on home prices can also be explained by looking at the area affected by the flood event. In the dataset, only 2% of the sales records are within the 100-meter buffer of flood areas for 78.8 mm/hr intensity. For 130 mm/hr, the number increases to 26.5%. Thus, it seems that home buyers feel worse when they are part of only 2% of the population affected by a flood, rather than when a quarter of the city is under water. The actual driving force of the negative impact on home prices could be a combination of both frequency and the range of influence, but further evidence is needed to clarify.

Finally, this study contributes to the literature by dealing simultaneously with the endogeneity and heterogeneity problems through developing the SFE-GWR model. The results show that SFE-GWR successfully captures the existence of heterogeneity while controlling for endogeneity. Further investigation into the SFE-GWR model is strongly encouraged to address the following challenges. First, the model has the limitations involving the SFE and GWR models. Theoretically, SFE only addresses spatial autocorrelation that occurs outside of the selected spatial districts. Thus, spatial autocorrelation within the districts remains. For GWR, p-values should not be discussed for each local regression; however, this raises a concern of over-emphasizing trends that might not be statistically significant. Finally, results of GWR with SFE should be interpreted with caution. The SFE coefficient should be interpreted as the amount of difference from the district mean at the margin. The results of GWR with SFE should be interpreted in the same way, even though the scope of local regression is not consistent with the spatial districts.

This study also has several limitations concerning the data used. First, the flood risk mentioned in this study is based on the flood risk maps published by the city government. Theoretically, the flood risk is only accurate if we assume that the flood risk maps are precise enough to capture the real-life flood risk. Nevertheless, as the negative effects of flood risk did not change significantly change after the maps were published, the disclosed flood potential is likely close to peoples' perceptions of the flood risk before the disclosure, though there is no direct proof of this. Thus, the effect of flood risk in this study should be understood as the home buyers' attitudes towards perceived flood risk, not towards real flooding events. Second, the government blurred the location of residences included in property sales records that were collected in this study due to privacy concerns. Theoretically, this random blurring process only creates white noise and the distance-related coefficients generated by regressions in this study should remain unbiased. However, standard errors are likely to be overestimated. In other words, estimated significance in this study represents the lower bound. If no blurring occurred, some insignificant variables would likely become significant.

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