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Is Flood Risk Capitalized into Real Estate Market Value? A Mahalanobis-Metric Matching Approach to the Housing Market in Gyeonggi, South Korea

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Received: 12 September 2018; Accepted: 24 October 2018; Published: 1 November 2018

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Abstract: In this study, we investigate how far away and for how long past flooding affected single-family housing values in Gyeonggi, South Korea. In order to empirically explore the geographic and temporal extent of the effects, we adopt two analytical methods: random-intercept multilevel modeling and Mahalanobis-metric matching modeling. The analytical results suggest that the geographic extent of the discount effect of a flooding disaster is within 300 m from an inundated area. Market values of housing located 0–100, 100–200, and 200–300 m from inundated areas were lower by 11.0%, 7.4%, and 6.3%, respectively, than counterparts in the control group. The effect lasted only for 12 months after the disaster and then disappeared. During the first month, 1–3 months, and 3–6 months after a flood, housing units in the disaster-influenced area (within 300 m of the inundated area) were worth, on average, 57.6%, 49.2%, and 45.9% less than control units, respectively. Also, within the following 6 months, the discount effects were reduced to 33.2%. On the other hand, the results showed no statistically significant effects on market values more than 12 months after the disaster. By providing insights into how people perceive and respond to natural hazards, this research provides practical lessons for establishing sustainable disaster management and urban resilience strategies.

Keywords: natural disaster; housing price; random-intercept multilevel model; Mahalanobis-metric matching model

1. Introduction

Recent increases in extreme weather events, such as heat waves, heavy rains, and landslides, have gained worldwide attention. Such natural disasters have caused social and economic loss [1,2] and casualties on a substantial scale [3,4]. In South Korea, the amounts of property damage caused by natural disasters have nearly tripled in the years since 2000 (approximately 1694 million US dollars per year) as compared to those during the 1990s (approximately 618 million US dollars per year); fifteen times that of the 1960s (approx. 114 million US dollars per year) [5]. The Korean government projects that the equivalent cumulative damage will cost about 2.5 trillion US dollars by 2100 [6].

The fear of a natural disaster factors into criteria for choosing where to live. Damage to real estate properties from disasters incurs costs for repair and maintenance [7,8]. Increasing numbers of people have begun to consider the history and future likelihood of disasters in a neighborhood when purchasing properties, and the real estate prices in disaster-prone areas have been accordingly volatile [9,10]. In the U.S., for example, the rate of appreciation of housing prices in safer areas was roughly 15% higher than that in areas with higher risks of natural disasters over the 10 years from 2005 to 2015 [11].

Although many researchers have investigated the relationship between natural hazards and real estate market values, the main focus has been on analyzing the ex-post price change of the properties as a consequence of the disaster in question. Most such analyses showed that natural disasters negatively affected real estate prices [12–14], but some found conflicting or nonsignificant results [15–17]. Some studies attempted to compare the price impacts before and after the disaster [18,19], or the effect of disclosure of risk information, adopting a Difference-in-Differences (DID) approach [10,20]. The recognition or fear of natural hazards, however, is not fixed but changing over time, and consequently the effect on real estate is time variant [21,22]. Previous examples, such as Mt. Umyeon in Seoul and Tohoku earthquake and tsunami in Japan are some of the evidence supporting the argument [23–26].

Against this backdrop, this study investigates the effect of inundation on housing values, as a function of not only the proximity to flooded areas, but also of time elapsed since the event, in the case of inundations in Gyeonggi Province, South Korea, from 2008 to 2013. This reflects the presumably differing geographic and temporal extent to which potential homebuyers recognize the threat of such events. To better explore our research questions, we use highly efficient analytical approaches: Random-intercept multilevel modeling and Mahalanobis-metric matching modeling. By deciphering a complex process determining when and how much a disaster affects real estate markets, this study contributes to the extant literature and, furthermore, offers practical lessons for sustainable disaster management strategies in urban planning.

In the remainder of the section, we first provide a literature review, next explain methodology and data sources, and then present the analytical results. The article concludes with discussions of the research findings and policy implications.

2. Literature Review

Extant studies have investigated the relationship between natural hazards and real estate market values. Most of the research suggested that natural disasters negatively affected market values of housing and land. The repetitive destruction of properties by disaster incurred high repair cost and thus resulted in depreciation of property values [12–14]. The burden of rising prices for catastrophe insurance also had negative effects on housing prices [9,27]. Koo and Lee [7] revealed that the scale of price reductions was larger when more hazard information was released through mass media.

Some researchers, however, found conflicting results or failed to show significant links. After damage recovery had been completed and further improvement had been made relative to the original condition, the negative effect disappeared or even turned positive [15,17]. Furthermore, simply with the passage of time, the negative effects faded out as people forgot about the events [16,28]. Although residential properties close to rivers, oceans, or mountains are more vulnerable to floods, tsunamis, and landslides, respectively, that very proximity can also bring price premiums by providing valuable amenities, such as recreational opportunities and scenic views [14,29,30]. It is assumed that the risk of natural hazards might be offset by the advantages of such natural settings [31–33].

The extent of disasters' impact varies by time, frequency and severity of the events. Lamond and Proverbs [28] explained four trajectories of change in property values in response to natural disasters. First, when a weather event occurs in a low-risk area, property values temporarily decrease, but soon go up to original levels, because the probability of recurrence of the event is low. Second, in disaster-prone areas, occasional weather events do not stir the real estate market, since market prices already reflect the risk, or because a government guarantees compensation for the consequent loss through a mandatory catastrophic insurance system. Third, when weather events occur in areas with no previous experience of natural disasters, housing prices stay at a low level for a longer time, because potential homebuyers feel that the area is no longer a disaster-free zone. Fourth, market prices decrease temporarily and then go up even higher than before when local conditions are improved beyond the original condition through public efforts taken to restore damage and protect the area from similar future events. For example, housing prices near the landslide area of Mt. Umyeon in Seoul dropped temporarily for a year and then returned to the original level [26]. The reason for this short-duration impact is, presumably, that the subject area was not a disaster-prone district and people believed that the chance of the recurrence of such an event was low [34]. Moreover, city governments successfully carried out restoration of damage and added preventive measures, such as drains and retaining walls, all of which offset the negative influence of the natural disaster [35]. Likewise, after the 2011 Tohoku earthquake and tsunami in Japan, Tokyo's property values plunged for a few months and then gradually rebounded after recovery efforts [23–25]. The construction of a new subway line in Sendai drove housing prices up even higher than the level before the incident [36].

In order to compare the prices of real properties before and after natural disasters, recent studies have adopted a DID approach. It is revealed that real estate properties in high-risk areas experienced a higher discount in comparison to equivalent properties outside the areas after the disaster events [19,21,22,37]. Atreya and Ferreira [18], in the case of the 1994 flood in Albany, Georgia, U.S., found that inundated properties inside and outside the floodplain were discounted by 41% and 33%, respectively, compared to non-inundated properties outside the floodplain. Other researchers also showed that the average value of properties in flood-prone areas significantly decreased after the release of flood risk information to the public [10,18]. Rajapaksa, Wilson, Managi, Hoang, and Lee [20], in a study of Queensland, Australia, found that the release of flood risk maps reduced property values by 1–4%, whereas the impact of the actual floods was significantly larger, mounting to reduction by 18–19% of the original value.

A DID approach, however, has a methodological shortcoming. In DID, it is assumed that the observations in the treatment and control groups are identical and that the only difference is the treatment itself [38]. This assumption is easily violated when the sample size is large and the subject observations are heterogeneous [39]. For this reason, establishing an appropriate comparison group has been difficult [38–40].

3. Data Analysis

In this study, we hypothesize that the effect of inundation on housing value differs not only in relation to proximity to flooded areas, but also in relation to the time elapsed since the flooding. In analysis 1, we analyze the geographic extent within which the inundation event affects housing prices. In analysis 2, we investigate the varying magnitude of such effects by time, within the geographic extent identified in the preceding analysis. The former implies that the discount effect is observed in a certain geographic area where the direct or indirect threat of the events affects homebuyers' decisions. The latter implies that the homebuyers' recognition of such threats changes according to the nature of the disaster and the local context.

3.1. Site and Data

The study site is Gyeonggi Province in South Korea (Figure 1). Gyeonggi Province is the largest metropolitan area in South Korea and the one that has been urbanized most rapidly since the 1970s [41]. Gyeonggi Province contains approximately 32.5% urbanized areas, where concentrated wealth would be exposed to catastrophic events [42]. Because the region is on low-lying terrain and contains multiple rivers and watersheds, flooding has been an ongoing issue [41,43,44]. The study period is from January 2008 to December 2013 for analysis 1 and from 2010 to 2013 for analysis 2. In analysis 2, we investigate the effects of flooding for 24 months before each transaction, and thus we could not include housing units that were sold in 2008 and 2009. Figure 2 shows the temporal settings of the analyses. Although the investigation would be more thorough if the time frame were longer, an extended dataset was not publicly available.

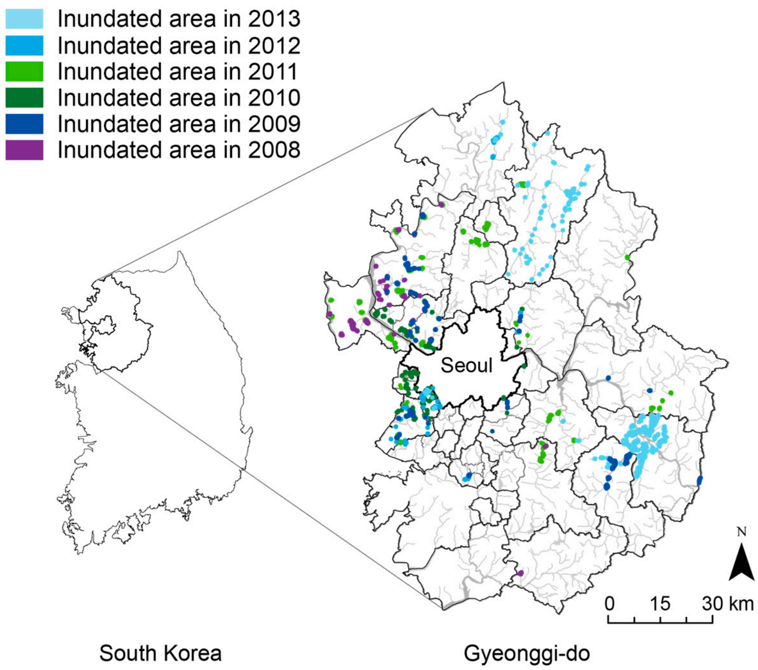

Figure 1. The boundary of the study area with reference to inundated areas in Gyeonggi Province, South Korea from 2008 to 2013.

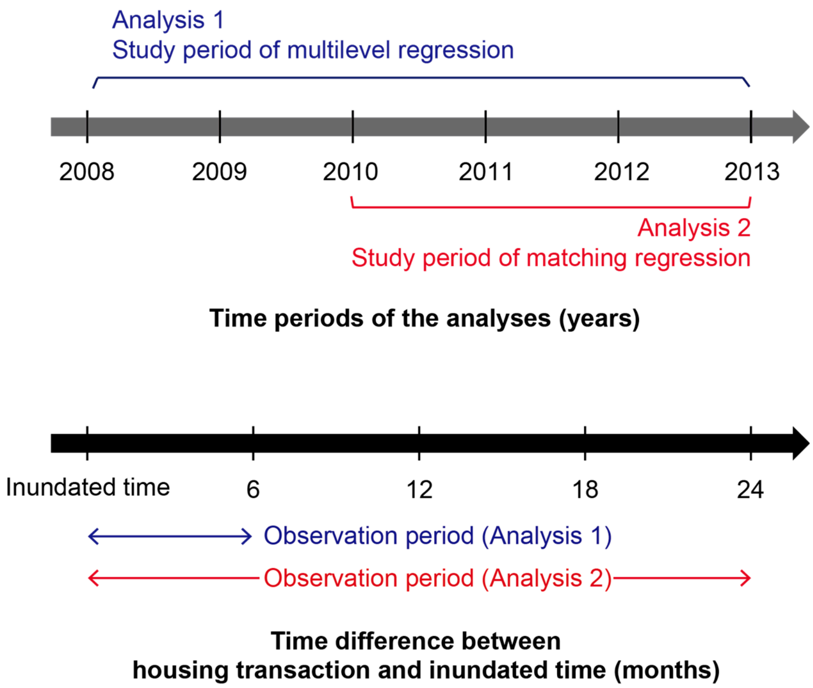

Figure 2. The temporal settings of the analyses.

We used two primary datasets. One provides the market transaction data, which was collected by the Ministry of Land Infrastructure and Transport during the study period. The sample includes 3024 transaction records of single-family housing, and all of those prices are adjusted to December 2013, based on the housing price index from the Korea Appraisal Board. The other primary dataset is the inundation map of the study site during the study period, which was obtained from the Korea Land and Geospatial Informatix Corporation.

Building attributes, such as net area and building age, were gathered from Korea's Ministry of Land Infrastructure and Transport. Location characteristics (the distance between each housing unit and other urban features, such as subways, bus stations, and schools) were sourced from the Population and Housing Census by Korea's National Statistical Office. Neighborhood information (socio-economic characteristics of neighboring residents, such as educational attainment, age composition, and population density, aggregated by census output area) and land attributes (elevation and topographic position index [TPI], a measure of terrain's relative concavity or convexity) were supplied by the same source.

3.2. Analytical Design

The dependent variable of both analyses is the log of transaction value of single-family housing units per square meter: ln(*market transaction value*). In analysis 1, the question variables are dummy variables, indicating the distance from the inundated area in 100 m incremental intervals. We specified the five dummy variables—0–100 m, 100–200 m, 200–300 m, 300–400 m, and 400–500 m—and compared them with the reference group indicating housing units beyond 500 m from the inundated area. In order to avoid potentially confounding factors of a distant location, we limited the analyses to the area within 1 km of the inundation. This approach could be an alternative to geographically weighted regression, one of the spatial analytical techniques for housing market segmentation based on explanatory variables [45].

In analysis 2, in order to investigate the time-varying effects, the sample was stratified by the time elapsed between the inundation and the transaction. First, we specified the first 6-month periods after the inundation—0–1 month, 1–3 months, 3–6 months—and then, analyzed the impacts per 6-month interval—6–12 months, 12–18 months, 18–24 months, and more than 24 months after the inundation. We also consider the repetitive occurrence of inundation events with dummy variables, indicating whether each housing unit repeatedly suffered damage during the intervals 0–6 months, 6–12 months, 12–18 months, and 18–24 months from the transaction time. Because the real estate market disturbance was generally the most obvious in 6-month intervals from 2008 to 2013 in Gyeonggi Province, we focused on that time frame in this analysis.

We also included four categories of covariates that could possibly affect the market value of property: structural, location, neighborhood and land characteristics. Structural characteristics indicate building attributes, such as net area (square meters) and building age. The information on the number of bedrooms and bathrooms, however, was excluded due to the high correlation with the net area of the housing units. Other structural variables, such as heating and cooling systems, as well as the presence of features (i.e., basement, fireplaces, and garages), are not included in the model, due to the data unavailability. This might remain as a limitation of our study. For location characteristics, we specified the distance to educational facilities (schools and universities), transportations facilities (subways, bus stations, and main roads), and other urban features and amenities, such as public institutions, shopping centers, major and local streams, and lakes or fountains. Location is one of the most critical factors determining the housing price in Korean context [46]. Also, to supplement the lack of structural variables, we have specified rather more extensive locational variables in the model. See Appendix A (Table A1) for the relevant correlation matrix of the location variables. As neighborhood characteristics, we included the ratio of people with more than a college degree, that of population older than 65 and less than 15, and population density. In terms of land characteristics, we included elevation and topographic position index (TPI). TPI is a measure of relative concavity or convexity of terrain, used to evaluate drainage conditions for a location. It is calculated by comparing the level of the subject terrain to the mean level of the adjacent terrains [47]. Last, fixed effects were added to indicate the year of transaction, to control for unobservable temporal heterogeneity. Since the Variance Inflation Factor (VIF) values for each independent variable were lower than 5, there were no multi-collinearity problem among the variables. See Appendix B for the table of the VIF values. The test result is available upon request from the authors. We attached the descriptive statistics in Appendix C.

3.2.1. Analysis 1: The Geographic Extent of the Flood Effect on the Housing Market

The market value of property is determined by complicated interactions of multiple components, including the site and neighborhood attributes, across the level of individual housing unit and the level of neighborhoods [48–50]. Multilevel modeling overcomes the limitation of traditional Ordinary Least Square (OLS), by permitting the assumption that individual units are not independent, but more similar, with closer proximity [30,51–53].

In this study, we adopted random-intercept multilevel modeling with two levels: Market value of property as level-1 and census tract as level-2. We can justify the use of multilevel modeling because 52.2% of variances is explained by the variance of the level-2 units (intraclass correlation). This regression model is shown in Equation (1a–c).

Level-1

$$\begin{aligned}\ln\left(Market\ Transaction\ Value_{ij}\right) &= \pi_{0i} + \pi_1 IND\_100_{ij} + \pi_2 IND\_200_{ij} + \pi_3 IND\_300_{ij} + \pi_4 IND\_400_{ij} \\ &+ \pi_5 IND\_500_{ij} + \beta_6 S_{ij} + \beta_7 L_{ij} + \beta_8 N_i + \beta_9 LD_{ij} + \gamma_{10t} \sum_{t=2008}^{2013} Year_{ijt} + \epsilon_{ij}\end{aligned} \tag{1a}$$

Level-2

$$\pi_{0i} = \theta_0 + v_{0i} \tag{1b}$$

Composite Model

$$\begin{aligned}\ln\left(Market\ Transaction\ Value_{ij}\right) &= \theta_0 + \pi_1 IND\_100_{ij} + \pi_2 IND\_200_{ij} + \pi_3 IND\_300_{ij} + \pi_4 IND\_400_{ij} \\ &+ \pi_5 IND\_500_{ij} + \beta_6 S_{ij} + \beta_7 L_{ij} + \beta_8 N_i + \beta_9 LD_{ij} + \gamma_{10t} \sum_{t=2008}^{2013} Year_{ijt} \\ &+ \epsilon_{ij} + v_{0i}\end{aligned} \tag{1c}$$

IND_100_{ij}: Dummy variable whether each housing unit is located within 100 m from the inundated area;
IND_200_{ij}: Dummy variable whether each housing unit is located 100–200 m from the inundated area;
IND_300_{ij}: Dummy variable whether each housing unit is located 200–300 m from the inundated area;
IND_400_{ij}: Dummy variable whether each housing unit is located 300–400 m from the inundated area;
IND_500_{ij}: Dummy variable whether each housing unit is located 400–500 m from the inundated area;
S_{ij}: A vector of structural factors;
L_{ij}: A vector of location factors;
N_i: A vector of neighborhood factors for census tract;
LD_{ij}: A vector of land factors;
$Year_{ijt}$: Fixed effect of transaction year (t = 2008, 2009, . . . , 2013);
ϵ_{ij}: Level-1 residual;
v_{0i}: Level-2 residual

3.2.2. Analysis 2: The Temporal Extent of the Flood Effect on Housing Market

The matching method is one of the simulated randomized experiments that enables the inference of causal effects on outcomes by equating or balancing the distribution of covariates in the treated and control groups [54,55]. Through a pairing of each observation receiving the treatment with a similar observation not receiving the treatment, this approach can establish an appropriate comparison group and yield unbiased treatment effects [38,56,57].

Unlike the conventionally used hedonic pricing model, a matching approach efficiently alleviates selection bias [58,59]. This approach assumes that the treatment is randomly assigned and that a vector of the observed covariates captures all the differences between the treated and control groups except the treatment [59,60]. By this approach, we could estimate the average treatment effect on the treated (ATET) by comparing the difference in the outcomes between the two groups [55,60].

The matching method is categorized by the principle of pairing between the two groups. In social science fields, it is common to use either a propensity score matching approach, in which the pairing is made by the conditional probability of the treatment given the covariates [61] or a Mahalanobis distance matching approach, in which pairing is made with the multivariate distance weighted by the covariance matrix [60]. The propensity score matching method is effective when treatment variable and covariates are highly relevant, whereas the Mahalanobis-metric matching method is more widely applicable to various empirical settings [62]. Meldrum [60] also emphasized that the process of minimizing the Mahalanobis distance between observable properties' characteristics closely resembles the real estate negotiation process between buyers and sellers of homes to determine a fair price by comparing properties that are similar in observable characteristics.

For these reasons, we adopted the Mahalanobis-metric matching modeling for this study. We paired each housing unit located within the disaster-influenced areas, which are determined in analysis 1 (treatment group), with a unit beyond those areas (control group), on the basis of the closest Mahalanobis distance between them. The Mahalanobis distance is calculated by the covariance matrix of the included variables in our study. This regression model is shown in Equation (2).

$$\text{ATET (Average Treatment Effect on the Treated)} = E(Y_1 - Y_0|A) = E(Y_1|A) - E(Y_0|A) \tag{2}$$

Y_1: The log of market transaction value within the disaster-influenced area;

Y_0: The log of market transaction value beyond the disaster-influenced area;

A: The covariance matrix of the included variables.

4. Findings

4.1. Results 1: The Geographic Extent of the Flood Effect on the Housing Market

Table 1 displays the results of random-intercept multilevel modeling examining the geographic extent of inundation on single-family housing values. Within six months after the inundation, the discount effect extended up to 300 m. Single-family housing units within 0–100 m, 100–200 m, and 200–300 m from the inundated areas were worth, on average, 11.0%, 7.4%, and 6.3% less than those located beyond 500 m from the inundated area (control group), respectively, controlling for variables specified in the model. At distances of 300–500 m from the inundated area, however, the price impact of the disaster was not observed at a 5% level of statistical significance. This means that, at a distance of more than 300 m from the inundated area, homebuyers may be indifferent to the record of past hazard and the possibility of the same event recurring in the future. Figure 3 shows the marginal discount effects in the five 100 m intervals. On the basis of this analytical result, we narrowed the study site to an area within 300 m of the inundated areas for analysis 2.

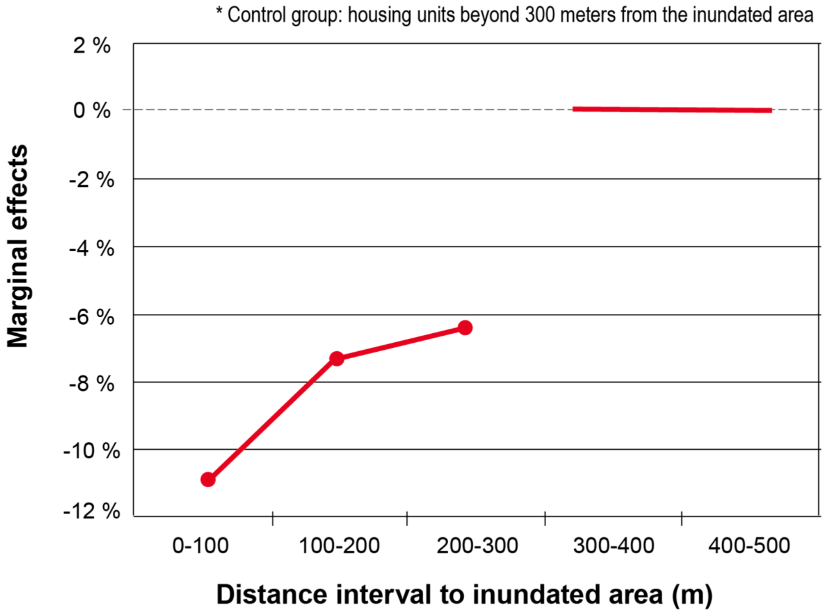

Figure 3. Marginal effects of proximity to the inundated areas by distance interval.

Table 1 also reveals that other characteristics significantly influence single-family housing values. The value of single-family housing units was negatively associated with higher net area. Larger houses are generally sold for lower unit price, which reflects the relatively lower construction unit costs for a larger housing unit, as well as the higher demand for a small and medium-sized housing unit than a larger one in Korean society [63]. The proximity to national streams, lakes, subways and universities were also positively associated with the housing values. While residential properties close to natural water bodies are generally more vulnerable to flooding events, such proximity could also bring price premiums by providing valuable amenities, such as recreational opportunities and scenic views [14,29]. We also found that the housing values increase significantly with the decreasing distance from subways and universities. The proximity to subways and universities positively affects surrounding property values as potential homebuyers consider a good transportation option and educational environment as an important factor in determining where to live [64]. Also, higher population densities were associated with lower housing market values, since it generates negative externalities, such as traffic congestions and higher level of noises [7]. The negative premium associated with higher elevation could be attributed to homebuyers' low preference for housing at higher altitudes, due to the inconvenient access to urban features and amenities [30].

Table 1. Results of the random-intercept multilevel regression model.

Variables	**Coefficient**
Question variable	
*IND*_100 (Within 100 m from inundated area; 1, if in this area, otherwise 0)	−0.110 *** (0.0320)
*IND*_200 (Within 100–200 m from inundated area; 1, if in this area, otherwise 0)	−0.0738 ** (0.0298)
*IND*_300 (Within 200–300 m from inundated area; 1, if in this area, otherwise 0)	−0.0631 ** (0.0312)
*IND*_400 (Within 300–400 m from inundated area; 1, if in this area, otherwise 0)	−0.0220 (0.0310)
*IND*_500 (Within 400–500 m from inundated area; 1, if in this area, otherwise 0)	−0.0333 (0.0334)
Structural variables	

Table 1. *Cont.*

Variables	Coefficient
Net area	−0.00152 *** (0.000119)
Building age	0.00122 (0.000890)
Location variables	
Distance to national stream	-1.68×10^{-5} *** (2.47×10^{-6})
Distance to local stream	-1.19×10^{-5} (8.16×10^{-6})
Distance to lake/fountain	-1.72×10^{-5} *** (4.74×10^{-6})
Distance to main roads	-1.56×10^{-5} (6.76×10^{-5})
Distance to subway station	-1.94×10^{-5} *** (2.88×10^{-6})
Distance to bus station	-6.90×10^{-5} (0.000101)
Distance to school	-5.65×10^{-6} (3.75×10^{-5})
Distance to university	-1.06×10^{-5} *** (3.09×10^{-6})
Distance to public institution	-2.87×10^{-5} (2.47×10^{-5})
Distance to shopping center	-5.40×10^{-6} (3.87×10^{-6})
Neighborhood variables	
Percentage with high education	−0.0201 (0.0497)
Percentage more than 65 years old	−0.655 * (0.239)
Percentage less than 15 years old	0.239 * (0.124)
Population density	-2.13×10^{-6} *** (5.98×10^{-7})
Land variables	
Elevation	−0.00166 ** (0.000739)
Topography position index (TPI)	0.00699 (0.00456)
Time fixed effects	YES
Constant	6.070 *** (0.0714)
Random effects	
$\Sigma\mu$ $\Sigma\varepsilon$ ρ	0.371 (0.0112) 0.355 (0.00544) 0.522 (0.0182)
Observations	3024
Number of groups	1161

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. Results 2: The Temporal Extent of the Flood Effect on the Housing Market

Table 2 presents the results of Mahalanobis-metric matching analysis examining the temporal extent of inundation disaster on single-family housing values. Within a month after inundation, the value of single-family housing units within 300 m from an inundated area (treatment group) declined by 57.6% compared to housing units with similar characteristics located beyond 300 m from the inundated area (control group). Also, within 1–3 months and 3–6 months after the inundation, the discount effects were reduced to 49.2% and 45.9%. Within 6–12 months after the events, housing units in the treatment group were sold on average for 33.4% less than the control units. Beyond 12 months after the disaster, however, we did not observe a statistically significant difference in property values between those two groups. In sum, flooding influences the surrounding real estate market negatively for 12 months after an event.

Figure 4 illustrates the time-varying effects of inundation on single-family housing units within 300 m of the flooded zone by time interval—0–1 month, 1–3 months, 3–6 months, 6–12 months, 12–18 months, 18–24 months, and more than 24 months after flooding in Gyeonggi, South Korea.

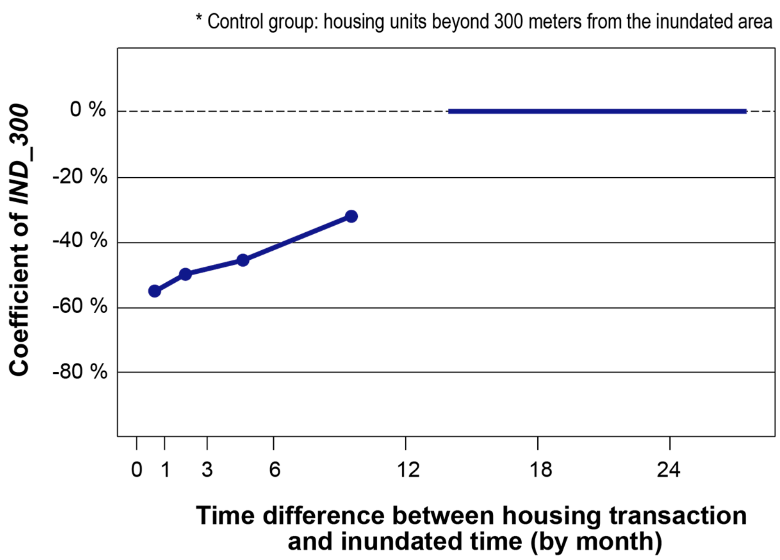

Figure 4. Impact changes of inundation on single-family housing units within 300 m from the inundated area.

Table 2. Results of Mahalanobis-metric matching model.

Time Difference (between Housing Transaction and Inundated Time)	0–1 month	1–3 months	3–6 months	6–12 months	12–18 months	18–24 months	>24 months
Treatment group	Housing units within 300 m from inundated area						
Control group	Housing units beyond 300 m from inundated area						
ATET (Avg treatment effect on the treated)	−0.576 **	−0.492 **	−0.459 **	−0.332 **	0.209	−0.0403	−0.00222
Std. error	0.193	0.197	0.207	0.159	0.137	0.280	0.0736
95% CI upper bound	−0.955	−0.879	−0.865	−0.644	−0.0595	−0.598	−0.146
95% CI lower bound	−0.198	−0.105	−0.0528	−0.0201	0.478	0.509	0.142
Sample size	1907	1907	1907	1907	1907	1907	1907
Number of the treated samples	61	101	124	235	192	154	189
Number of the untreated samples	1846	1806	1783	1672	1715	1753	1718

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The analytical results can be summarized as follows. The negative effect of previous flooding on single-family housing extends from the flood site to 300 m and lingers through 12 months, with a higher magnitude for the first month and lessened magnitudes for 1–3 months, 3–6 months, and the next 6–12 months. This means that the price impacts of natural disasters vary according to the progress of restoration work after the previous event or the potential homebuyers' recognition of future risk of a similar natural event.

5. Discussion

The purpose of our research is to reveal how far away and for how long the occurrence of flooding affects single-family housing values, in the case of inundation in Gyeonggi Province, South Korea. Within 6 months after an inundation, single-family housing units 0–100, 100–200, and 200–300 m from the inundated areas were worth, on average, 11.0%, 7.4%, and 6.3% less than control units located beyond 500 m from the inundated area, controlling for all other factors. Sales prices of housing units beyond 300 m from the inundated areas, however, did not show any effect of the disaster. The effect of such natural events lasted for about one year, with diminishing magnitude. Within a month after the inundation, single-family housing units located within 300 m from the inundated area were worth, on average, 57.6% less than control units located beyond this area. Also, within 1–3 months and 3–6 months after the inundation, the discount effects were reduced to 49.2% and 45.9%. And, for the following 6 months, the discount effect was reduced to 33.2%. It then dissipated beyond 12 months.

The analytical results demonstrate that the price impacts of natural disasters could vary by time. The resilience of housing market values may be attributed to the government's active maintenance and repair works in the affected area. Gyeonggi Province, for example, has continuously restored and reformed the environments of neighborhoods damaged by disaster through the construction of new infrastructure, such as rain gutters, retaining walls, and backwater prevention facilities [65]. From 2009 to 2016, the government spent about 102 million US dollars on restoration projects, amounting to more than twice the cost of the actual damage, about 51 million US dollars [66]. As mentioned in the literature review, this effort helps potential homebuyers to feel secure against future natural events [28].

Another conjecture might be that recognition of natural hazards is offset by other types of neighborhood improvement [53]. For example, when a city government of Gyeonggi Province, Gwangmyeong City, issued plans to develop a new public rental housing complex and mixed-use community in flood-prone areas, the market prices of properties in the existing neighborhoods increased drastically, although the potential risk of flooding remained unaddressed [65,67]. If potential homebuyers place a higher priority on an improved living environment than on the risk of natural hazard, they may purchase the properties at higher prices than before [21,28].

In order to minimize the duration of the negative influence of disasters on the housing market, governments should make such efforts continuously, without interruption by the public budget shortage. The establishment of mandatory catastrophe insurance is one of the potential solutions [68,69]. Although the Korean government has long operated a catastrophe insurance and recovery support system, the enrollment rate for the insurance is very low, and the level of support is only minimal [70]. On the other hand, the U.S. government has completely obligated property owners to take mandatory flood insurance and has paid the cost of damage recovery [68,71].

If information about disaster risk is not available to the public, however, the price impacts of natural hazards might be distorted [7,72]. In most advanced countries, such as the U.S., France, and Japan, governments have made public the records of previous disasters and the future likelihood of disasters under a natural hazard disclosure law [73,74]. The Korean government, however, has been reluctant to make this information public, due to strong civil complaints that such action would depreciate real estate values in disaster-prone areas [75].

For long-term and sustainable disaster management, governments should organize and develop collaborative governance structures involving a broad range of stakeholders throughout the process of developing and managing cities [76]. In particular, an effective disaster management and response system requires rapid utilization of information from different sources; thus, government departments and local agencies should cooperate with each other in developing big data and computer simulation technologies for predicting and preventing the events [77]. For example, the Korean government has introduced a Smart Big Board service, which is a new disaster management system for alerting people in real time to disaster situations, by integrating big data information, including smartphone GPS (Global Positioning System) data, social media contents, and satellite imagery and CCTV (Closed Circuit Television) information [77,78].

By examining a complex picture of when and how much disasters affect real estate markets and, furthermore, how people perceive and respond to natural hazards, this paper offers valuable implications for the establishment of sustainable disaster management and urban resilience strategies. Using a similar and extended procedure, the home-buyers' perception of the future risk and real estate market reactions could be easily simulated. With an understanding on the amount that accrues to the markets by the public works for the restorations and improvements, and by analyzing cost-benefit ratio, public authorities could understand that such expense could also be an investment. Those works not only address the problems, but also add values to the society by securing residents' sense of safety and security.

Considering the differing geographic and temporal extent of the disaster impacts, regulators could determine the coverage of the disaster prevention and management measures, including catastrophe insurance policies and programs. Policymakers could establish rational criterion to determine the geographic and temporal extent the disaster insurance covers, and the amount of premium the potential homebuyers have to pay. This policy ensures a fairer risk management mechanism through which the payers for the restorations could receive the further benefits associated with the improve environment and enhanced sense of security [79].

Author Contributions: E.J. conceptualized the study, conducted formal analyses, and wrote the original draft. H.Y. advised in the process of the conceptualization and analysis, reviewed and edited the draft, and acquired the research fund.

Funding: This research was funded by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea under grant number [NRF-2017S1A5A8020226].

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Correlation matrix of location variables.

	(1)	(2)	(3)	(4)	(5)
Distance to national stream (1)	1				
Distance to local stream (2)	0.185 ***	1			
Distance to lake/fountain (3)	−0.0453 ***	−0.000112	1		
Distance to main roads (4)	−0.0853 ***	−0.0583 ***	0.0254 ***	1	
Distance to subway station (5)	0.118 ***	−0.119 ***	0.139 ***	0.248 ***	1
Distance to bus station (6)	0.0369 ***	−0.00286	0.0280 ***	0.371 ***	0.283 ***
Distance to school (7)	0.00663	−0.0681 ***	0.0882 ***	0.490 ***	0.399 ***
Distance to university (8)	−0.0934 ***	−0.0914 ***	0.228 ***	0.236 ***	0.412 ***
Distance to public institution (9)	0.0565 ***	−0.0734 ***	0.0520 ***	0.476 ***	0.458 ***
Distance to shopping center (10)	0.0216 ***	−0.146 ***	0.0418 ***	0.338 ***	0.567 ***
	(6)	(7)	(8)	(9)	(10)
Distance to national stream (1)					
Distance to local stream (2)					
Distance to lake/fountain (3)					
Distance to main roads (4)					
Distance to subway station (5)					
Distance to bus station (6)	1				
Distance to school (7)	0.474 ***	1			
Distance to university (8)	0.273 ***	0.409 ***	1		
Distance to public institution (9)	0.458 ***	0.742 ***	0.437 ***	1	
Distance to shopping center (10)	0.358 ***	0.563 ***	0.544 ***	0.582 ***	1

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix B

Table A2. Variance inflation factor (VIF) values for independent variables.

Variable	VIF	1/VIF
Net area	1.48	0.675
Building age	1.18	0.851
Distance to national stream	1.28	0.783
Distance to local stream	1.15	0.870
Distance to lake/fountain	1.18	0.844
Distance to main roads	1.44	0.695
Distance to subway station	1.72	0.583
Distance to bus station	1.43	0.698
Distance to school	2.75	0.364
Distance to university	1.67	0.597
Distance to public institution	2.78	0.360
Distance to shopping center	2.25	0.444
Percentage with high education (%)	1.10	0.910
Percentage more than 65 years old (%)	2.10	0.476
Percentage less than 15 years old (%)	1.06	0.945
Population density (person/km^2)	1.62	0.617
Elevation	1.48	0.678
Topography position index (TPI)	1.07	0.934
Mean VIF	1.60	

Appendix C

Table A3. Descriptive statistics of variables.

Variables	Mean	Standard Deviation	Min	Max
Ln (Market transaction value) (10,000 Korean Won/m^2)	5.203	0.517	3.213	7.376
Distance to inundated area (m)	434.5	281.1	0	998.6
Net area (m^2)	203.7	129.3	15.10	1293
Building age (year)	23.58	12.51	0	113
Distance to national stream (m)	6866	4009	63.70	22,907
Distance to local stream (m)	1996	1485	17.81	5507
Distance to lake/fountain (m)	1984	1857	62.03	23,795
Distance to main roads (m)	129.1	134.7	2.711	1297
Distance to subway station (m)	2621	3584	12.78	28,324
Distance to bus station (m)	139.5	102.1	3.197	1139
Distance to school (m)	354.7	319.7	22.76	2710
Distance to university (m)	3370	4217	114.6	29,368
Distance to public institution (m)	359.8	436.9	8.951	4528
Distance to shopping center (m)	1469	2361	8.274	24,283
Percentage with high education (%)	0.451	0.205	0.104	0.947
Percentage more than 65 years old (%)	0.107	0.0615	0	0.556
Percentage less than 15 years old (%)	0.140	0.0695	0	0.881
Population density (person/km^2)	27,350	19,562	39.80	130,067
Elevation (m)	31.08	19.12	0	144
Topography position index (TPI)	−0.303	1.796	−6.827	19.11

References

1. Porfiriev, B. Economic issues of disaster and disaster risk reduction policies: International vs. Russian perspectives. *Int. J. Disaster Risk Reduct.* **2012**, *1*, 55–61. [CrossRef]
2. Torresan, S.; Critto, A.; Rizzi, J.; Marcomini, A. Assessment of coastal vulnerability to climate change hazards at the regional scale: The case study of the north adriatic sea. *Nat. Hazards Earth Syst. Sci.* **2012**, *12*, 2347–2368. [CrossRef]

3. Lioubimtseva, E. A multi-scale assessment of human vulnerability to climate change in the aral sea basin. *Environ. Earth Sci.* **2015**, *73*, 719–729. [CrossRef]
4. Zahran, S.; Tavani, D.; Weiler, S. Daily variation in natural disaster casualties: Information flows, safety, and opportunity costs in tornado versus hurricane strikes. *Risk Anal.* **2013**, *33*, 1265–1280. [CrossRef] [PubMed]
5. Lee, K.J. 'Heavy Rain' is the Main Cause of Natural Disaster. Available online: http://www.seoul.co.kr/news/newsView.php?id=20110802010013 (accessed on 26 October 2018).
6. Chae, Y.R.; Jo, H.J.; Choi, S.Y. The Economic Analysis of Climate Change in Korea. Korea Environment Institute. Available online: http://www.prism.go.kr/homepage/theme/retrieveThemeDetail.do?leftMenu=110&cond_brm_super_id=NB000120061207100091168&research_id=1480000-201200211 (accessed on 26 October 2018).
7. Koo, H.S.; Lee, H.Y. The effect of the disaster hazards information on residential property prices. *Seoul Stud.* **2015**, *16*, 57–74.
8. Vranken, L.; Van Turnhout, P.; Van Den Eeckhaut, M.; Vandekerckhove, L.; Poesen, J. Economic valuation of landslide damage in hilly regions: A case study from Flanders, Belgium. *Sci. Total Environ.* **2013**, *447*, 323–336. [CrossRef] [PubMed]
9. Harrison, D.; Smersh, G.T.; Schwartz, A. Environmental determinants of housing prices: The impact of flood zone status. *J. Real Estate Res.* **2001**, *21*, 3–20.
10. Votsis, A.; Perrels, A. Housing prices and the public disclosure of flood risk: A difference-in-differences analysis in finland. *J. Real Estate Financ. Econ.* **2016**, *53*, 450–471. [CrossRef]
11. RealtyTrac. 43 percent of U.S. Homes with an Estimated Market Value of $6.6 Trillion in Counties with High Natural Disaster Risk. Available online: https://wpnewsroom.realtytrac.com/news/realtytrac-2015-u-s-natural-disaster-housing-risk-report (accessed on 26 October 2018).
12. Egbenta, I.; Udo, G.; Otegbulu, A. Using hedonic price model to estimate effects of flood on real property value in lokoja, nigeria. *Ethiopian J. Environ. Stud. Manag.* **2015**, *8*, 507–516. [CrossRef]
13. Ismail, N.H.; Karim, M.Z.A.; Basri, B.H. Flood and land property values. *Asian Soc. Sci.* **2016**, *12*, 84–93. [CrossRef]
14. Zhang, Y.; Hwang, S.N.; Lindell, M.K. Hazard proximity or risk perception? Evaluating effects of natural and technological hazards on housing values. *Environ. Behav.* **2010**, *42*, 597–624. [CrossRef]
15. Montz, B.E. The effects of flooding on residential property values in three New Zealand communities. *Disasters* **1992**, *16*, 283–298. [CrossRef] [PubMed]
16. Mueller, J.; Loomis, J.; González-Cabán, A. Do repeated wildfires change homebuyers' demand for homes in high-risk areas? A hedonic analysis of the short and long-term effects of repeated wildfires on house prices in Southern California. *J. Real Estate Financ. Econ.* **2009**, *38*, 155–172. [CrossRef]
17. Tobin, G.A.; Montz, B.E. The flood hazard and dynamics of the urban residential land market. *J. Am. Water Resour. Assoc.* **1994**, *30*, 673–685. [CrossRef]
18. Atreya, A.; Ferreira, S. Seeing is believing? Evidence from property prices in inundated areas. *Risk Anal.* **2015**, *35*, 828–848. [CrossRef] [PubMed]
19. Bin, O.; Landry, C.E. Changes in implicit flood risk premiums: Empirical evidence from the housing market. *J. Environ. Econ. Manag.* **2013**, *65*, 361–376. [CrossRef]
20. Rajapaksa, D.; Wilson, C.; Managi, S.; Hoang, V.; Lee, B. Flood risk information, actual floods and property values: A quasi-experimental analysis. *Econ. Rec.* **2016**, *92*, 52–67. [CrossRef]
21. Atreya, A.; Ferreira, S.; Kriesel, W. Forgetting the flood? An analysis of the flood risk discount over time. *Land Econ.* **2013**, *89*, 577–596. [CrossRef]
22. Kousky, C. Learning from extreme events: Risk perceptions after the flood. *Land Econ.* **2010**, *86*, 395–422. [CrossRef]
23. Housing Japan. A History of Tokyo Real-Estate Prices. Available online: https://housingjapan.com/buy/history (accessed on 26 October 2018).
24. Real Estate Japan Inc. Tohoku Residential Property Prices Continue Steady Recovery. Available online: https://resources.realestate.co.jp/news/tohoku-residential-property-prices-continue-steady-recovery (accessed on 26 October 2018).
25. Ryu, J.M. Tsunami of Japan's High-Rise Apartment after the Great Earthquake. Available online: http://www.asiae.co.kr/news/view.htm?idxno=2017111719183376041 (accessed on 26 October 2018).

26. Jung, E.; Yoon, H. The impact of landslide disaster on housing prices—A case study of the landslide of mt. Umyeon in Seoul, Korea. *J. Korea Plan. Assoc.* **2017**, *52*, 153–170. [CrossRef]
27. Bin, O.; Kruse, J.B.; Landry, C.E. Flood hazards, insurance rates, and amenities: Evidence from the coastal housing market. *J. Risk Insur.* **2008**, *75*, 63–82. [CrossRef]
28. Lamond, J.; Proverbs, D. Does the price impact of flooding fade away? *Struct. Surv.* **2006**, *24*, 363–377. [CrossRef]
29. Eves, C. The impact of flooding on residential property buyer behaviour: An England and Australian comparison of flood affected property. *Struct. Surv.* **2004**, *22*, 84–94. [CrossRef]
30. Yoon, H. Transforming the economic value of hillside housing—A case study of Seoul, South Korea. *Urban For. Urban Green.* **2017**, *24*, 35–44. [CrossRef]
31. Atreya, A.; Czajkowski, J. Graduated flood risks and property prices in Galveston county. *Real Estate Econ.* **2016**, 1–38. [CrossRef]
32. Daniel, V.E.; Florax, R.J.; Rietveld, P. Flooding risk and housing values: An economic assessment of environmental hazard. *Ecol. Econ.* **2009**, *69*, 355–365. [CrossRef]
33. Lee, D.B. Differential impacts of floodplains on home prices: A housing submarket approach. *J. Korea Plan. Assoc.* **2015**, *50*, 223–251. [CrossRef]
34. Baek, S.K. A Year after the Landslide of mt. Umyeon. Available online: http://news.mk.co.kr/newsRead.php?year=2012&no=353432 (accessed on 26 October 2018).
35. Kim, Y.J. Completion of Restoration Work of the Landslide of mt. Umyeon in New Year's Day. Available online: http://www.munhwa.com/news/view.html?no=20121228010710430970060 (accessed on 26 October 2018).
36. Jeon, Y.S. Japanese Real Estate Market Wriggles with the Signs of Economic Recovery. Available online: http://magazine.hankyung.com/business/apps/news?popup=0&nid=01&c1=1014&nkey=2017040301114000231&mode=sub_view (accessed on 26 October 2018).
37. Naoi, M.; Seko, M.; Sumita, K. Earthquake risk and housing prices in Japan: Evidence before and after massive earthquakes. *Reg. Sci. Urban Econ.* **2009**, *39*, 658–669. [CrossRef]
38. Rosenbaum, P.R.; Rubin, D.B. The bias due to incomplete matching. *Biometrics* **1985**, *41*, 103–116. [CrossRef] [PubMed]
39. Hawkins, S.S.; Baum, C.F. Invited commentary: An interdisciplinary approach for policy evaluation. *Am. J. Epidemiol.* **2016**, *183*, 539–541. [CrossRef] [PubMed]
40. Choi, Y.; Yoon, H.; Jung, E. Do silver zones reduce auto-related elderly pedestrian collisions? Based on a case in Seoul, South Korea. *Accid. Anal. Prev.* **2018**, *119*, 104–113. [CrossRef] [PubMed]
41. Choi, C. Does urbanization indeed increase disaster damages? *J. Environ. Policy* **2010**, *9*, 3–27. [CrossRef]
42. Kang, S.J. Distribution Characteristics and Countermeasures of Storm Damage Area in Gyeonggi-do. Gyeonggi Research Institute. Available online: http://www.gri.re.kr/%EA%B8%B0%ED%83%80-5/?pageno=16&ptype2=&sc=&sv=&limit=10&searchcode=&pcode=&brno=4364&prno=3160 (accessed on 26 October 2018).
43. Hong, J.; Hwang, J. Analysis on the change of regional vulnerability to flood. *Korea Environ. Inst.* **2006**, *5*, 1–18.
44. Kang, S.; Jung, J. Study on the distribution characteristics of storm damage area: The case of gyeonggi-do. *J. Korean Soc. Civ. Eng.* **2012**, *32*, 507–517. [CrossRef]
45. Manganelli, B.; Pontrandolfi, P.; Azzato, A.; Murgante, B. Using geographically weighted regression for housing market segmentation. *Int. J. Bus. Intell. Data Min.* **2014**, *9*, 161–177. [CrossRef]
46. KAB Real Estate Research Institute. *Korea Real Estate Market Report*. 2017. Available online: https://www.kab.co.kr/kab/research/archive/03periodical05List.jsp (accessed on 26 October 2018).
47. Jenness, J. Topographic Position Index. Available online: http://www.jennessent.com/arcview/tpi.htm (accessed on 26 October 2018).
48. Lee, C.R.; Park, K.H. A multi-level longitudinal analysis of the land price determinants. *J. Korean Geogr. Soc.* **2013**, *48*, 272–287.
49. Lee, S.H.; Chun, K.K. A study of the influences of urban infrastructure on housing prices: A hierachical linear model. *J. Korea Assoc.* **2012**, *47*, 193–204.
50. Yoon, H. When and where do we see the proximity effect of a new park?—A case study of the dream forest in Seoul, Korea. *J. Environ. Plan. Manag.* **2018**, *61*, 1113–1136. [CrossRef]

51. Christens, B.D.; Speer, P.W. Contextual influences on participation in community organizing: A multilevel longitudinal study. *Am. J. Community Psychol.* **2011**, *47*, 253–263. [CrossRef] [PubMed]
52. Hoffman, L. Multilevel models for examining individual differences in within-person variation and covariation over time. *Multiv. Behav. Res.* **2007**, *42*, 609–629. [CrossRef]
53. Jung, E.; Choi, Y.; Yoon, H. The impact of the Gyeongui line park project on residential property values in Seoul, Korea. *Habitat Int.* **2016**, *58*, 108–117. [CrossRef]
54. Jung, H. Impact study of afterschool programs for high school students with below-basic proficiency level. *J. Korean Educ.* **2013**, *40*, 49–69.
55. Stuart, E.A. Matching methods for causal inference: A review and a look forward. *Stat. Sci. A Rev. J. Inst. Math. Stat.* **2010**, *25*, 1–21. [CrossRef] [PubMed]
56. Hagen, T.; Fitzenberger, B. Mikroökonometrische methoden zur ex-post-evaluation. *Hartz-Gesetze–Methodische Ansätze zu einer Evaluierung, ZEW Wirtschaftsanalysen Bd* **2004**, *74*, 45–72.
57. Rubin, D.B. Teaching statistical inference for causal effects in experiments and observational studies. *J. Educ. Behav. Stat.* **2004**, *29*, 343–367. [CrossRef]
58. Ho, D.E.; Imai, K.; King, G.; Stuart, E.A. Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Anal.* **2007**, *15*, 199–236. [CrossRef]
59. Stuart, E.A. Estimating causal effects using school-level data sets. *Educ. Res.* **2007**, *36*, 187–198. [CrossRef]
60. Meldrum, J.R. Floodplain price impacts by property type in Boulder county, Colorado: Condominiums versus standalone properties. *Environ. Resour. Econ.* **2016**, *64*, 725–750. [CrossRef]
61. Wang, Y.; Xin, L.; Li, X.; Yan, J. Impact of land use rights transfer on household labor productivity: A study applying propensity score matching in Chongqing, China. *Sustainability* **2016**, *9*, 4. [CrossRef]
62. Zhao, Z. Using matching to estimate treatment effects: Data requirements, matching metrics, and monte carlo evidence. *Rev. Econ. Stat.* **2004**, *86*, 91–107. [CrossRef]
63. Kim, S. Large Sized Apartment Price per 3.3 m2 Is Cheaper than Small Sized One. Available online: http://news.heraldcorp.com/view.php?ud=20140519000088&md=20140519081030_BK (accessed on 26 October 2018).
64. Sah, V.; Conroy, S.J.; Narwold, A. Estimating school proximity effects on housing prices: The importance of robust spatial controls in hedonic estimations. *J. Real Estate Financ. Econ.* **2016**, *53*, 50–76. [CrossRef]
65. Park, Y.S. 'Whenever It Rains, Floods Sweep over the Country', a Backflow of Flooding Prevention Projects. Available online: http://www.kyeongin.com/main/view.php?key=20170821010006397 (accessed on 26 October 2018).
66. Jin, H.K. Gyeonggi Province Has Suffered 500 billion Won Damage from Natural Disaster after 2009. Available online: http://news1.kr/articles/?2952289 (accessed on 26 October 2018).
67. Heo, S. "From Inundated Area to Public Housing". The Selection of 68 Sites for the Urban Regeneration New Deal Project. Available online: http://www.hani.co.kr/arti/economy/economy_general/823514.html (accessed on 26 October 2018).
68. Lee, J.; Kim, M. Study on improvement of natural disaster insurance. *Sogang Law J.* **2015**, *4*, 31–64.
69. Manganelli, B.; Vona, M.; De Paola, P. Evaluating the cost and benefits of earthquake protection of buildings. *J. Eur. Real Estate Res.* **2018**, *11*, 263–278. [CrossRef]
70. Shin, D.H. A study on the risk distribution of natural hazards and the role of government. *J. Insur. Stud.* **2005**, *45*, 49–75.
71. Shin, D.H. Review of the compulsory storm and flood insurance and policy implications. *J. Insur. Financ.* **2008**, *54*, 77–107.
72. Lamond, J.; Proverbs, D.; Hammond, F. The impact of flooding on the price of residential property: A transactional analysis of the uk market. *Hous. Stud.* **2010**, *25*, 335–356. [CrossRef]
73. Pope, J.C. Do seller disclosures affect property values? Buyer information and the hedonic model. *Land Econ.* **2008**, *84*, 551–572. [CrossRef]
74. Troy, A.; Romm, J. Assessing the price effects of flood hazard disclosure under the California natural hazard disclosure law (ab 1195). *J. Environ. Plan. Manag.* **2004**, *47*, 137–162. [CrossRef]
75. Woo, H.W. There Was No Warning of Heavy Rain. Available online: http://news.kbs.co.kr/news/view.do?ncd=2165702 (accessed on 26 October 2018).

76. Childers, D.; Cadenasso, M.; Grove, J.; Marshall, V.; McGrath, B.; Pickett, S. An ecology for cities: A transformational nexus of design and ecology to advance climate change resilience and urban sustainability. *Sustainability* **2015**, *7*, 3774–3791. [CrossRef]
77. Choi, S.H.; Park, Y.J.; Shim, J.H. Strengthening of disaster management ability through big data utilization. *J. Korean Soc. Civ. Eng.* **2015**, *63*, 21–28.
78. Park, Y.; Jeong, I.; Seo, J.; Kim, J. A study on the construction of a disaster situation management system in korea based on government 3.0 directive. *WIT Trans. Built Environ.* **2015**, *150*, 59–66.
79. Kim, J.; Park, J.; Yoon, D.K.; Cho, G.-H. Amenity or hazard? The effects of landslide hazard on property value in Woomyeon nature park area, Korea. *Landsc. Urban Plan.* **2017**, *157*, 523–531. [CrossRef]