Does Flooding Lower Property Values? An Empirical Evidence from Jakarta, Indonesia

MSc Spatial, Transport, Environmental Economics (STREEM)

The School of Business and Economics

Vrije Universiteit, Amsterdam

Ashila Ghitha – 2788071

Supervisor: Eric Koomen

June 2023

Table of Contents

Abstract

Flooding in Jakarta has occurred more frequent while housing prices are also exceptionally high. This paper analyzes the impact of flooding on property values in Jakarta in 2014 using different flood indicators. Based on the hedonic pricing model, this paper confirms that flooding negatively correlates with monthly house rent in Jakarta. Flood severity, best represented by the average water depth, decreases the monthly house rent by around 0.5 percent for a one-centimeter higher water depth. Flood frequency, proxied by flood recurrence and period of inundation, contributes to a lower monthly house rent by, on average, 7-12 percent. The results are most robust when utilizing a period of inundation as the flood indicator. These findings generate three main implications: (1) people tend to underestimate the value of an environmental attribute, such as flooding, but put more value on housing characteristics, (2) the demand for housing in prone-flood areas is very high such that people prefer to stay especially in business areas, and cover the damage cost from flooding, and (3) house rent in Jakarta could be lowered by improving maintenance for flooding infrastructure so those potential damages incorporated by landlords in a rent price decrease.

JEL Classification: Q51, Q54, R31

Keywords: flood, hedonic price model, environmental economics, housing.

1. Introduction

Natural disasters cause severe damage socially and economically. Hallegate et al. (2010) specified that natural disasters cause direct costs, such as damages to the built environment, and indirect economic costs. Indirect costs, defined in their paper as output losses, are the cost of reductions in economic productivity because of natural disasters. Natural disasters can even impact the housing market if the disaster causes a scarcity of alternative housing in the area (Hallegate et al., 2010). With the ongoing climate change concern, increasing world temperature will also cause more natural disasters, such as windstorms, droughts, and floods, in the future (Stern, 2007).

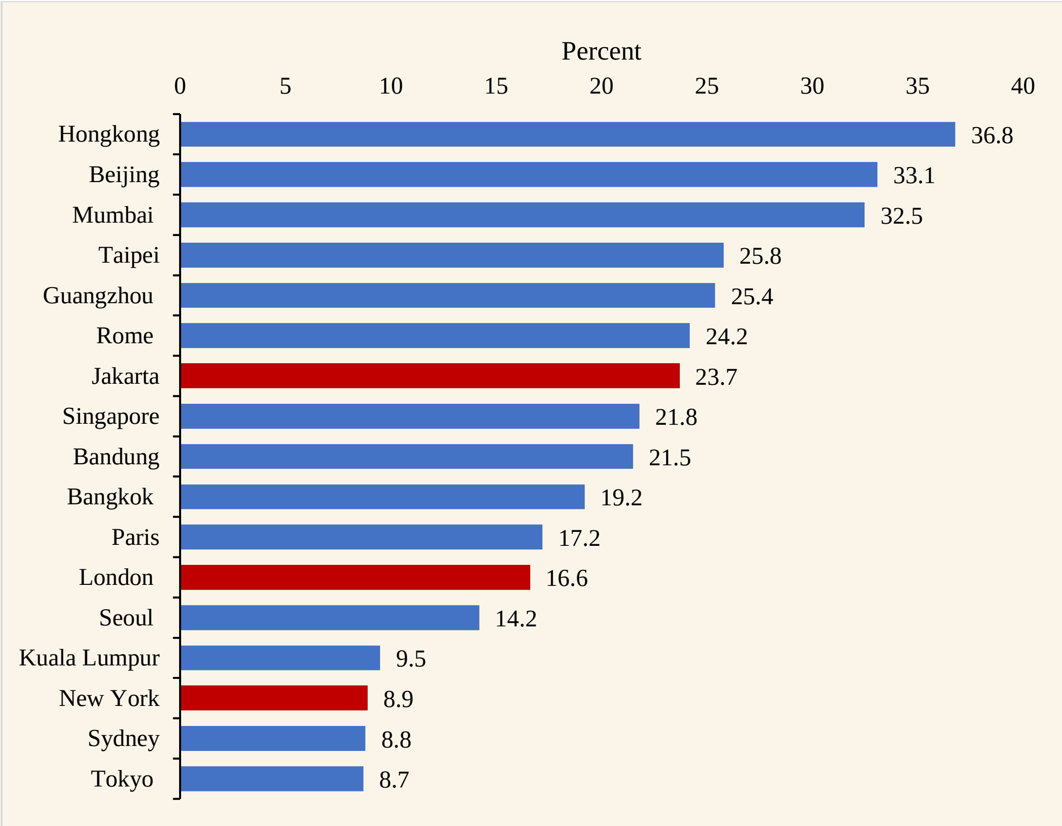
Flooding, one of the most common natural hazards, dominated the total number of catastrophic events recorded in 2021, with overall losses of around 74.4 billion US Dollars, the second highest after windstorms (CRED, EM-DAT, 2021). Compared to the rest of the world, this phenomenon is becoming more common in many developing countries with megacities, such as Asian cities like India, China, and Indonesia. These countries tend to have large concentrations of people in urban areas hence there will be more people exposed to flood risks as floods become more frequent and intense (Luo et al., 2015). The United Nations Habitat (n.d.) noted that 45 percent of the global urban population lives in Asia and the urban population growth in Asia is expected to grow by 50 percent in 2050. However, most of these urbanization processes are usually followed by urban challenges due to the lack of infrastructure and urban services (Cohen, 2004). Around 250 million people in the East Asia Pacific region, the largest slum population region in the world, are living with limited access to essential services, poor-quality housing, and are at risk of flood hazards (Baker & Gadgil, 2017). The low-income groups, in particular, will mostly live in slum areas with high exposure to flood risk due to the lower land prices on the riverbanks (Marschiavelli, 2008). Hence, the uncontrolled urbanization process and the rise in climate change will lead to more populations being exposed to flood risk in developing countries.

Jakarta, the capital city of Indonesia, is one of the biggest megacities in the world, with around 11 million population, and has become one of the fastest-growing cities in the world (Martinez & Masron, 2020). Since 1976, the population of Jakarta has more than doubled (NASA, Earth Observatory, 2005), and the percentage of the working-age population is projected to reach 71 percent in 2030 (Bappenas, 2013, p.40). However, this megacity's fast-growing urbanization process has become uncontrollable for many years and caused significant infrastructure problems such as urban sprawl, massive traffic congestion, informal settlements, and widespread flooding (World Bank, 2011).

Flooding has become Jakarta's primary concern since years ago due several reasons. First, the low and flat alluvial plain through which 13 rivers flow makes Jakarta prone to flooding during the Monsoon season (United Nations Climate Change [UNCC], 2022). The city is also exposed to rising sea levels since 40 percent of the city is below the sea level (Burge, 2022), which is expected to intensify in the future (Garschagen et al., 2018). Second, many informal settlements in Jakarta are located on the riverbanks, which low-income groups inhabit (Marschiavelli, 2008). With 45 percent of Jakarta's population still experiencing multiple deprivations (Wright, 2015), a large part of Jakarta's population is undeniably exposed to the risk of flooding. Furthermore, years of accumulated garbage in the waterways added by the inefficient draining system makes flood stick around longer than it should have (Sedlar, 2016). These factors cause Jakarta very prone to flooding, making the city expected to drown by 2050 (Kulp & Strauss, 2019). Climate observers and researchers also emphasized that the flood problem in Jakarta is expected to keep increasing due to the factors above and the rise in climate change (Cahya, 2020; JBA Risk Management, 2020).

However, amidst the high risk of flooding, the house price in Jakarta in general is very high. Numbeo (2015) and Roberts et al. (2015) found that the house price-to-income ratio in Jakarta is much higher than in New York and London, as shown in Figure 1. Kemang, a neighborhood in South Jakarta, is known as one of the most elite neighborhoods in Jakarta, with a house price of around 30 million Rupiah per square meter (or around 2000 US Dollars) (Brighton, 2022). Despite the high housing prices, this wealthy neighborhood is also very prone to flood. In 2016, the governor of DKI Jakarta claimed that the Kemang area is essentially a basin serving a natural water inlet (Brahm, 2016). The latest flood occurrence in 2022 still impacted the neighborhood, where the water level reached 130 centimeters (CNN, 2022). These interesting facts raise the question of whether flooding affects where people live in Jakarta, looking at the city's house prices pattern.

Figure 1. The Ratio of House Price to Income



Source: Author's Illustration based on Numbeo (2015)

The striking fact about Jakarta's house price raises the following research question that this study aims to answer: "Does the increase in flood severity and flood frequency influence the increase in house prices in Jakarta?" With the prediction that the city will drown in 30 years while flood problems do not seem to vanish anytime soon, it is interesting to see whether there are correlations between floods and the very high house price. This study also gives a different perspective than previous US studies about flood impacts on house prices which did not focus on flood frequency. Using hedonic price analysis, this study attempts to estimate the impact of Jakarta's flooding in 2014 on monthly housing rent. Four proxies are used to estimate flood severity and frequency: water depth, area affected (RW-based), flood recurrence, and period of inundation. These different measurements will help future research and policymakers in deciding on the measurement of flood and how it can differ the impact on house prices.

The rest of the paper is organized as follows: Section 2 will discuss the impact of flooding on house prices and how flood frequency and severity may have different impacts. Section 3 describes the empirical strategy and data descriptions. Section 4 provides the results and analysis. Section 5 discusses the findings and limitations, while the final section concludes.

2. Literature Review

2.1 Impacts of Flood in Jakarta

Several studies have looked into the economic impacts of flood events in Jakarta. Budiyono et al. (2015) developed the first city-scale quantitative flood risk assessment in Jakarta, called the damage scanner model, and found an approximately US$321 million annual expected damage from river flooding in Jakarta. The model combines hazards and exposure maps to find the maximum damage that would occur on the identified land use class. Budiyono et al. (2016) used the same model to estimate future flood risk by including physical and socioeconomic change projections. They found a median increase in flood risk of 180 percent by 2030, with land subsidence contributes the largest. Januriyadi et al. (2018) also projected the future flood risk, which they found that the combination of climate change in urbanization in Jakarta will amplify flood risk by 322 percent - 402 percent in 2050.

Wahab and Tiong (2017) took a different approach to estimate the impact of the 2013 January floods in Jakarta using a multi-variate residential flood loss estimation model. The authors concluded that as the water flood level increases, the losses tend to rise, with the tangible loss for the residential sector in Jakarta being larger in higher-income areas. Only one study examines the relationship between flooding and house price in Jakarta. Cobian and Resosudarmo (2019) estimated the impact of the 2007 flood in Jakarta using hedonic pricing analysis and found that a one percent higher flood water level is associated with a 0.124 percent lower monthly housing rental price. They also calculated the willingness to pay to permanently remove the flood, which is much higher than the annual cost. Continuing this study, Cobian et al. (2022) analyzed the demand for flood insurance in Jakarta using the distance from a house to a floodgate station as a proxy of basis risk. The results indicate a decrease in the demand for flood insurance as the degree of basis risk and premium increase. The demand also declines at higher levels of risk aversion due to the inadequate coverage provided by a product with basis risk.

Nevertheless, numerous studies about flood and house prices have been conducted mostly in developed countries, in particular in the United States (Atreya & Ferreira, 2015; Bin & Polasky, 2004; Bin & Landry, 2013; Ortega & Taspinar, 2018; among others). These studies examined how flood events after disastrous hurricanes decreased property values around the impacted area. They also often differentiate the impact on houses located in flood-prone neighborhoods compared to houses in rarely exposed to flood areas, in which they found a decreasing premium in the area with a low probability of getting flooded (Atreya et al., 2013; Bin & Landry, 2013). The following sub-section will discuss these studies in more detail while focusing on the impact of different flood characteristics on house prices. Still, it is important to note that the flood events in the United States have different characteristics than those in Jakarta, as they are more of a rare occurrence than a monthly phenomenon.

2.2 Flood Severity

Tobin and Newton (1986) firstly pointed out that land values will vary spatially across floodplains depending on the spatial characteristics of the flood event. When the flood experience becomes more severe, the structural damage caused by it will be higher and more apparent to its capitalization process. The structural damages from the flood decrease the value of the land, and as the damage is too significant, the reduced land value lasts before it can recover to the pre-flood value. Their study was confirmed by Montz and Tobin (1988), who focused on how different levels of water depth influence property values. Houses that were flooded up to 10 feet (or around 300cm) were sold lower than the median selling price compared to houses that suffered 18 inches (or around 45cm) of water. Prices also recovered faster for houses experiencing lower water depth, suggesting that different flood depth leads to different capitalization and recovery process for the real estate market.

In another case, Ortega and Taspinar (2018) differentiate the impact of flooding in New York that came from Hurricane Sandy in 2012 based on the level of property damage. They classified houses in the flood zone into three different levels of damage. Using the Difference-in-Difference method, their estimations show that the more damaged the property was, the sharper the reduction in house prices following the flood event. Price drops between 17 percent and 22 percent immediately after the storm for damaged properties before converging to the same level as the non-damaged properties at 9 percent within five years. Besides using the damage variable, Ortega and Taspinar (2018) also utilized the flood depth for each point of observation. They classified the properties that were not flooded, flooded below 5.5 ft, and above 5.5 ft. The results resembled the one when using the damage variable.

Besides using flood depth and damage, a flood's severity could also be measured by the duration of inundation or the number of days the flood lasts in an area. Atreya and Ferreira (2015) emphasized the importance of the inundated area when estimating the impact of the flood on house prices following the flood in 1994 in Albany, Georgia, the United States. The authors found that inundated floodplain properties were discounted by 41 percent and 33 percent for inundated properties outside the floodplain. Interestingly, their estimations became insignificant when the properties were in the floodplain but not inundated by the flood. Their results suggest that homeowners are more likely to experience physical damages following a flood, and people are more responsive to what they have experienced directly. In a more explicit inundation estimation, Beltrán et al. (2019) used flood duration to measure flood impact on property values in England. First, they compared the impact of inland flooding on the price of inundated and non-inundated properties, where they found a reduced house price of 31.3 percent from inland flooding. Then, they also assessed how the duration of inundation also impacts property values. Properties within an area where the period of inundation lasted longer show a greater price discount but at a smaller magnitude.

2.3 Flood Frequency

Another important flood characteristic when looking at the impact of a flood on house prices is the frequency of the flood. If the area suffers from repeated flooding, the land values will stick at low levels since the market does not have time to recover before the next flood event (Tobin & Newton, 1986). However, when the flood event is rare in the area, land values will decline drastically following the flood but eventually return to pre-flood levels. These imply that house prices will depend on the frequency of the flood event and the ability of the market to recover.

The most straightforward way to investigate the flood frequency impact is by looking at the variation in the number of flood occurrences in an area. Beltrán et al. (2019) and Lamond et al. (2010) studied the impact of flooding in the United Kingdom based on the flood history. In the UK, flood events can be regarded as small in terms of their hazard and vulnerability, i.e., the scale and population affected. On an economic scale, however, the financial losses from flooding in the UK are significant (Scheuren et al., 2008). Both literatures found that the more frequent the flood occurrence, the more impact the flood has on property values. On average, properties that were flooded more than once in 2000 had a price discount of 15 percent, while properties that were flooded more than three times had a maximum of 35 percent discount (Lamond et al., 2010). Similarly, Beltrán et al. (2019) estimations show an additional reduction of 8.6 percent in house prices for houses that have been flooded multiple times between 1995 and 2014. House buyers are reacting to their flood experience, and frequent floods prevent the market from recovering to the initial pre-flood property values (Lamond et al., 2010; Tobin & Newton, 1986).

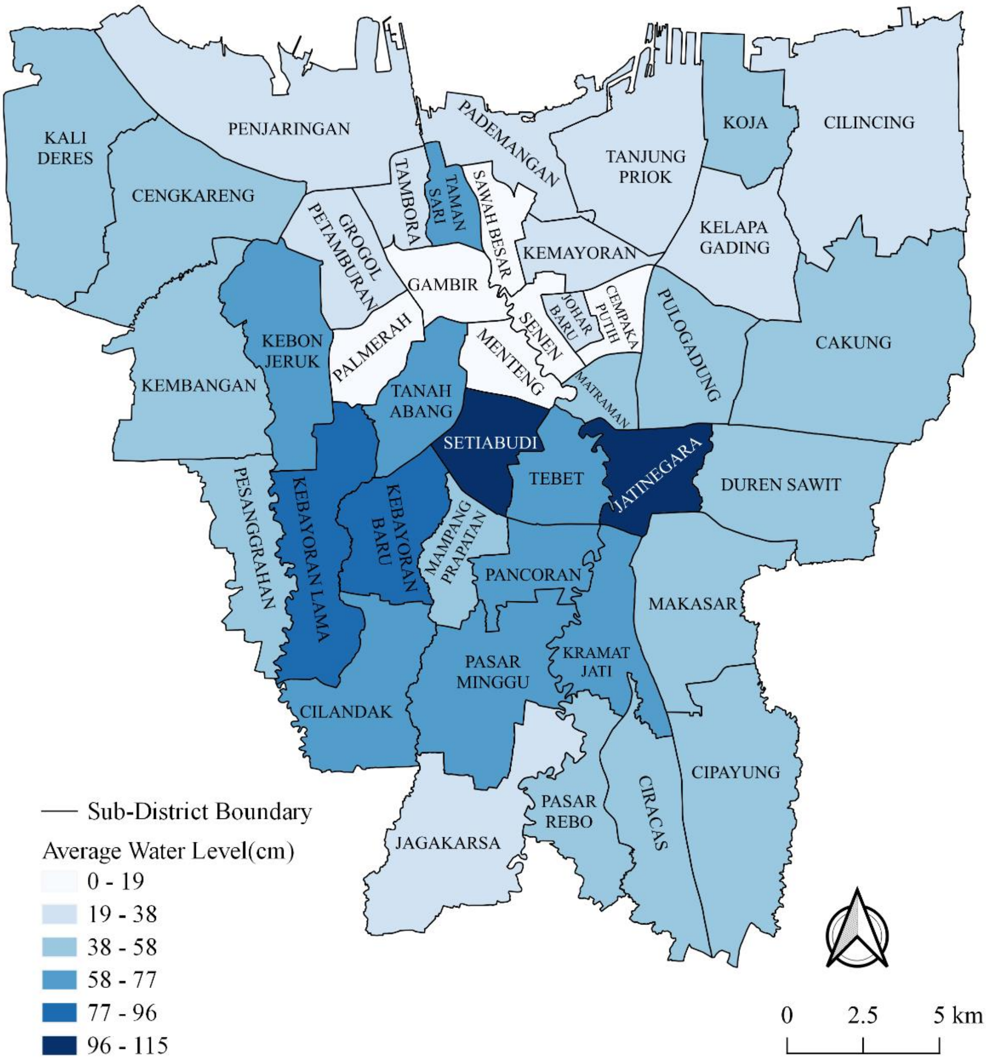
In the case of a very rare occurrence of flooding, Hirsch and Hahn (2018) take the city of Regensburg in Germany as a case study on whether there is a significant relationship between flood risk and property rents. Severe events rarely impact the city, and in their study, the 2013 flood event impacted the city as every 20 years event. Their estimations show that the buying price for one square meter of living area is, on average, EUR299 lower if the property is in a flood risk area with the rent price discounts, on average, at 1.8 percent. This is a very low figure compared to other estimates found in other studies, showing that the rare occurrence of flooding only impacted house prices at a marginal level.

3. Data and Methodology

3.1 Study Area

Jakarta Province is located on the northwest coast of Java at the mouth of the Ciliwung, a canalized river over 100km long that flows from the hinterland of Java, crisscrosses the city, and then empties into the Bay of Jakarta. The province is also often merged with the overlapping neighboring cities, known locally as Jabodetabek (an acronym of Jakarta, Bogor, Depok, Tangerang, and Bekasi), transforming Jakarta into a megacity with 31.24 million population, the second-most populous urban area in the world after Tokyo. Figure 2 illustrates Jakarta at the sub-district level. The map shows the distribution of floods in Jakarta in 2014 based on the average water level. Most parts of Jakarta were affected by flooding in 2014, where the most severe water depth was found in Jatinegara and Setiabudi.

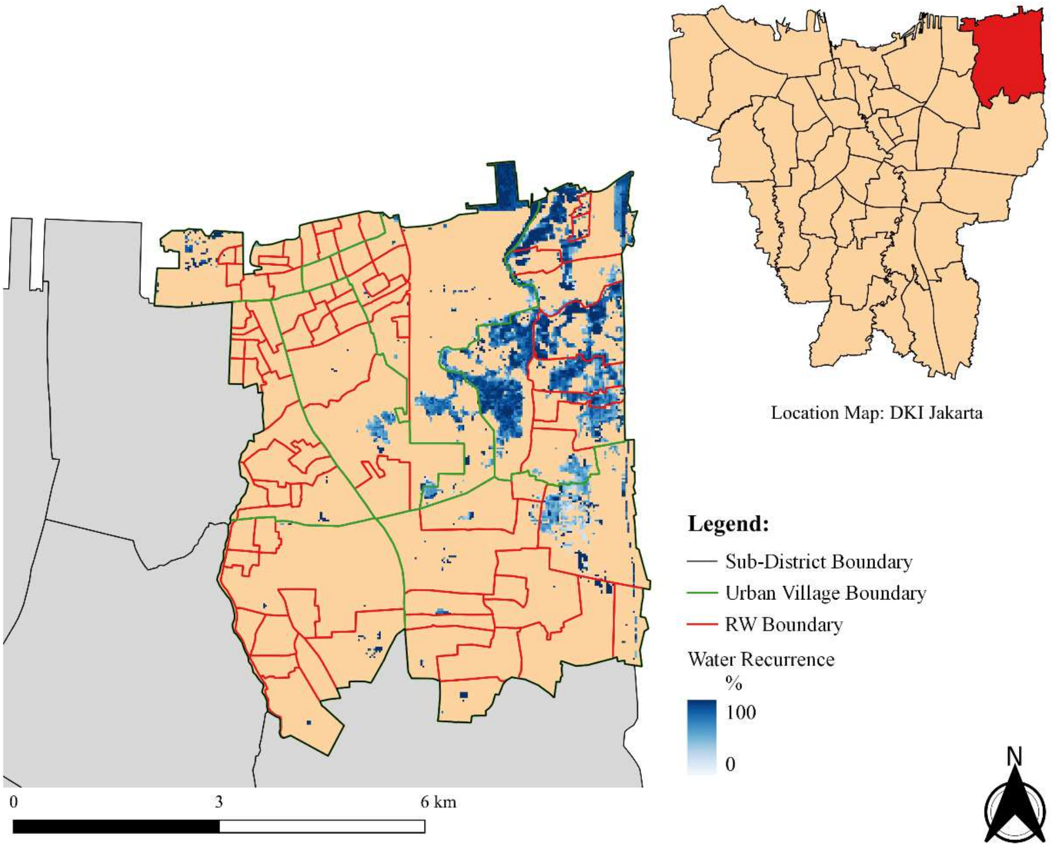
Figure 2. Map of Jakarta and Flood Water Level in 2014



Source: Own Illustration based on Open Street Map (OSM) and BPBD

Jakarta, a capital city of Indonesia, is a special province. It consists of five cities (or *Kota*) and one district (or *Kabupaten*), namely: Central Jakarta, South Jakarta, North Jakarta, West Jakarta, East Jakarta, and Kepulauan Seribu. City and district are headed by a mayor and *Bupati*, respectively. On average, each city manages 8 sub-districts (or Kecamatan) while each sub-district administers 7 urban villages (or *Kelurahan*, a specific village term for an urban area). A sub-district is headed by a *camat* while a *lurah* heads an urban village. Each urban village, on average, consists of 10 RW (or *Rukun Warga)*, a lower administration level under the urban village, headed by the head of RW. Each RW covers 16 RT (or *Rukun Tetangga*), the lowest administrative level in Jakarta or at the neighborhood level, headed by the head of RT managing 160 households. Detail administrative hierarchy of Jakarta province is presented in Appendix A1. However, due to the data availability, the lowest administrative level in this study is RW. Figure 3 shows an example of the administration boundaries and how it covers water recurrence in Cilincing, a sub-district in North Jakarta. Cilincing consists of 7 urban villages and 86 RW.

Figure 3. Jakarta's Administration Boundary Illustration: Cilincing



Source: Own Illustration based on Open Street Map and Global Surface Water

3.2 Data Description and Sources

This paper's primary data source is the Indonesian Family Life Survey 2014, or IFLS5. The Indonesian Family Life Survey (IFLS) is an ongoing longitudinal data socio-economic survey, which has been conducted five times in 1993, 1997, 2000, 2007, and the latest in 2014. The survey covers 83 percent of the Indonesian population, or over 30,000 individuals residing in 13 of the 27 provinces in the country. On each of the 13 selected provinces, they randomly selected 321 enumeration areas (EAs or an area of a village) and randomly selected households again on each EAs.

In the IFLS5 data, 945 households with house rents were recorded for Jakarta, covering 42 sub-districts across five districts in Jakarta[1]. From these observations, 377 (39.89 percent) households owned the house, 280 (29.63 percent) households occupied the house, 285 (30.16 percent) households rented the house, and others (0.32 percent). Occupying a house implies staying in other people's houses without paying the rent, for instance, occupying their parents' home. Households who rented the house were asked to report their monthly rent, and for either self-owned or occupied houses, they were asked how much they were willing to pay (WTP) if they were to rent the house. Therefore, for the rest of this study, I classify the dataset into two types: 285 observations with real rent and 660 observations for households with WTP Rent.

For housing characteristic variables, I follow the variables used in the basic hedonic pricing model available in IFLS5 (Cobian & Resosudarmo, 2019; Yusuf & Koundouri, 2005; Yusuf & Resosudarmo, 2009): the size of the house, number of rooms, roof/walls/floors materials, and the existence of toilet with a septic tank. The variables for roof/walls/floors materials are dummies where each building material will equal to one if the house is made of good materials (Soenarto Rosidin, 2021): ceramic/marble/granite/stone for floors; masonry (cement/prefabricated bricks) for outer walls; concrete/roof tiles/shingles/asbestos for roofs. Each housing characteristic[2] is expected to give a property a positive value.

The analysis also includes two spatial characteristics variables that are expected to impact property values. First, the variable distance to the center of Jakarta shows how accessible the area is to the employment area. This variable is expected to be negatively correlated with property value since the further away from the workplace, the higher the cost of traveling, such as time and money (Glaeser & Kahn,

[1] The exclusion of Kepulauan Seribu District in IFLS5 still validates the survey since the share of the population of Kepulauan Seribu was only 0.22 percent of Jakarta's population (BPS, 2014).

[2] Cobian and Resosudarmo (2019) included two additional housing characteristics: a dummy for a water source inside the house and a dummy for a sizeable yard. Although both coefficients are positive, these two variables were never significant in their paper and this study; hence, I decided to drop them.

2004; Yusuf & Koundouri, 2005). The distance variable is calculated in the QGIS using map data from Open Street Map and Lapak GIS, and measured as the distance from the centroids of each Jakarta sub-district to the National Monument. The other spatial characteristic is the proportion of high-educated households in the sub-district. The education variable is calculated from SUSENAS (National Social Economic Survey) as the number of households with College (D1, D2, and D3) and University (Bachelor, Master, and Doctorate) Degrees in a sub-district over the total number of households in that sub-district. A higher fraction indicates more high-educated people living in that sub-district, hence more knowledgeable people who understand flood risk and houses (Cobian & Resosudarmo, 2019; Yusuf & Resosudarmo, 2009).

The other data source used in this study is the Regional Disaster Mitigation Agency for Jakarta (BPBD), which provided a monthly flood report 2014. The agency delivered monthly recapitulation data of flood incidents, which includes the number of groups of households affected, the number of evacuees, water levels, and the period of inundation with exact dates. The data are available until RW and RT levels. No floods occurred in September and October; hence there is no data for these two months.

From the BPBD data, four possible flood variables can be used in the analysis: two are proxies for flood severity, and the other two are for flood frequency. First, the flood severity can be measured by calculating the average area affected based on the RW administration level, aggregated at the sub-district level. The result will show how much damage the flood caused in the form of the affected area of RW in the sub-district. Water depths are also often used to determine flood severity (Cobian & Resosudarmo, 2019; Montz & Tobin, 1988; Ortega & Taspinar, 2018). The BPBD reported the water depths as a range of minimum and maximum water levels in each flooded village. The water depth is calculated by determining the median[3] of each minimum and maximum water depth and aggregating it to the sub-district level in each month before averaging both water depths for 2014 on each sub-district. I also consider using either dummy or categorical dummy variables for these different levels

[3] The median is used instead of the average when merging the water level data into the sub-district level in each month in 2014 because there is a wide range of water levels in either minimum or maximum water levels. Using the median will avoid extreme water level values.

of water depths based on the maximum water depth in each sub-district. However, isolating the dummy variables only with the maximum water depth does not give consistent results[4] as it is not an accurate measure. Meanwhile, the average water depth includes both minimum and maximum flood water depth which will capture the flood variation within the sub-district.

The last two flood variables focused on flood frequency. The flood recurrence is calculated as the total number of months a flood has occurred in a sub-district over 12 months. The higher the fraction, the more frequently the area was flooded in 2014. Another way to look at flood frequency is by examining the duration of inundation in that sub-district. Although Beltrán et al. (2019) used the period of inundation to look at the flood intensity, this study will utilize the period of inundation to indicate how frequently the flood affects the sub-district. The variable is calculated as the total number of days in 2014 the sub-district was inundated by a flood over the total number of days in 2014. All flood variables are expected to impact property value negatively.

3.3 Empirical Strategy

This study uses a hedonic property price approach to estimate flood severity and frequency effects on property values. This model was pioneered by Andrew Court in 1939 in implementation to cars and was formalized by Rosen (1974), who introduced a link between the hedonic price theory and standard economic theory. Hedonic pricing gives a value to house attributes and determines its implicit prices on house prices, including the value of environmental amenities (Beron et al., 1997; Brookshire et al., 1985; Harrison et al., 2001). Flooding is seen as an attribute that could affect the willingness to pay for a house, so studies have previously looked at the premium differential across properties varying in their flood hazards (Atreya & Ferreira, 2015; Bin & Polasky, 2004; MacDonald et al., 1987). Following the hedonic pricing model, the regression equation for this cross-section study is as follows:

$$lnRent_i = \beta_0 + \beta_1 H_1 + \beta_2 k_2 + \beta_3 Flood + \varepsilon \quad (1)$$

[4] The regression results when using either dummy or categorical dummies showed a negative relationship with house rent when the water depth is less than 60cm but positive when it is above 60cm. Changing the specifications still gives inconsistent results, which would make using dummy variables unreliable.

Where $lnRent_i$ is the log of monthly house rent, either real rent or WTP rent; H_1 is a vector of housing attribute variables consisting of house size, number of rooms, building materials (floor, outer wall, and roof), and the existence of a toilet with septic tank; k_2 is a vector of spatial variables consist of the distance to Jakarta center and high-educated households; $Flood$ is the flood indicator with either water depth, area affected, flood recurrence, or period of inundation; and ε is the error term that is assumed to be independently and identically distributed (i.i.d).

The log transformation in the dependent variable is used to minimize the possibility of heteroscedasticity that often arise in house price variables due to the significant variation (Gujarati, 1995; Wooldridge, 2013). Following previous studies, the monthly house rent is transformed into log for the rest of the analysis (Atreya & Ferreira, 2015; Bin & Polasky, 2004; Bin & Landry, 2013; Cobian & Resosudarmo, 2019; Ortega & Taspinar, 2018). I also look into the distribution of the independent variables to observe other potential sources of heteroscedasticity. The distribution for house size and number of rooms are skewed towards zero, while the relation with distance to the center is usually non-linear. Hence these three variables are better transformed into a log. Figure 4 compares these three variables before the log transformation (left) and after transformed into log (right), where the distributions become closer to normal distribution.

Analyzing property values at the sub-district level inevitably would include some variations between sub-districts that may not be captured in equation (1) but affect house rent. For instance, South Jakarta's sub-districts always have the higher house rent due to the closeness to the main business districts, entertainment areas, and various transportation facilities. These variables, which would vary in other parts of Jakarta, are unobserved heterogeneity that needs to be controlled to avoid biased estimations. Fixed Effects (FE) is one way to resolve this since the method assumes that the differences among sub-districts can be accommodated from the differences in their intercepts (Allison, 2009; Bell & Jones, 2015). In a cross-section study, FE is applied to the regression by controlling the variation between sub-districts at the District level, one administration level higher than the sub-district level:

$$lnRent_i = \beta_0 + \beta_1 H_1 + \beta_2 k_2 + \beta_3 Flood + DistrictFixedEffects + \varepsilon_i \qquad (2)$$

Another methodology that should have been implemented in a hedonic model is by controlling the potential spatial dependence of properties. Neighboring properties are likely to share common unobserved location features, and the estimated model should control for spatial dependence with either spatial lag or spatial error model (Anselin & Florax, 1995; Atreya & Ferreira, 2015; Cobian & Resosudarmo, 2019). However, this study cannot implement either method due to the unavailability of the coordinates for the spatial weight matrix that is essential in the model.

Figure 4. Distribution of Independent Variables in Levels and Log Transformed

Source: Author's calculations from IFLS5, Open Street Map (OSM), and LapakGIS

3.4 Descriptive Statistics

Tables 1a and 1b present the descriptive statistics for the variables I use in this paper. Due to the availability of RT, RW, and urban village data, all household data are extracted at the sub-district level. As previously mentioned, two types of rent data are available: real rent with 285 observations and WTP rent with 659 observations. Using real rent would typically give more precise estimates as it avoids inconsistencies between imputed rent and actual data (Cobian & Resosudarmo, 2019; Yusuf &

Koundouri, 2005). However, as there are more observations in the WTP rent, I also estimate the data for WTP rent to investigate if there are any differences with real rent data in the analysis. The descriptive statistics in WTP rent are slightly different from real rent due to this dataset's higher number of observations. The maximum and the minimum values for spatial characteristics and flood indicators are the same as real rent since these variables are obtained at the sub-district level instead of the household level.

Table 1a. Summary Statistics: Real Rent

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable					
Monthly Rent (Rp)	285	568266.2	326668.6	29167	3333333
Monthly Rent (Log)	285	13.09334	0.6089027	10.28079	15.019
Housing Characteristics					
House Size (sqm)	285	28.856	32.043	4	360
House Size (Log)	285	3.058	0.744	1.386	5.886
Number of Rooms	285	2.944	1.43	1	11
Number of Rooms (Log)	285	0.949	0.539	0	2.398
Stone floor (1,0)	285	0.758	0.429	0	1
Masonry wall (1,0)	285	0.853	0.355	0	1
Good roof (1,0)	285	0.965	0.184	0	1
Toilet with Septic Tank (1,0)	285	0.681	0.467	0	1
Spatial Characteristics					
Distance to Jakarta Center (km)	285	8.754	4.589	1.1	18.632
Distance to Jakarta Center (log)	285	2.006	0.608	0.096	2.925
High-Educated HH	285	0.214	0.241	0.029	0.892
Flood Indicator					
Water Depth (cm)	285	43.035	23.103	0	115
Affected Area (RW)	285	0.038	0.037	0	0.273
Flood Recurrence	285	0.2	0.169	0	0.833
Period Inundation	285	0.096	0.093	0	0.425

Source: Author’s calculation from IFLS5, SUSENAS, OSM, LapakGIS, and BPBD

The average monthly real rent in Jakarta is around Rp500,000, with the lowest rent at around Rp30,000 and the highest at around Rp3,000,000. Having rent at 30,000 rupiahs (or around 2 US Dollars) per month may sound very cheap, but this is realistic if we consider the very small houses with less than ten sqm house size in slum areas of Jakarta. Compared to the real rent data, the WTP rent has a higher imputed rent. The average rent in WTP data is around Rp1,500,000 monthly, or three times larger than the average monthly real rent. It shows here that people tend to report an overestimated rent price when asked about their willingness to pay if they were to rent the house, as suggested by Yusuf and Koundouri (2005). The maximum WTP Rent is Rp40,000,000 (or around 2700 US Dollars) per month, which may sound very expensive, but this is the true value[5] for the case in wealthy areas of Jakarta. Similarly, two observations with a house size of 600 sqm located in Kebayoran Lama and Tanah Abang are also normal, while a house with 40 rooms is possible, considering there are some houses in Jakarta used for dormitories. One observation in WTP Rent data is dropped because the house size is very large, 4100 sqm, which is unrealistic[6].

Table 1b. Summary Statistics: WTP Rent

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable					
WTP Monthly Rent (Rp)	659	1449292	2757233	83330	40000000
WTP Rent (Log)	659	13.6958	0.8478626	11.33056	17.504
Housing Characteristics					
House Size (sqm)	659	78.206	77.591	3	600
House Size (Log)	659	3.964	0.918	1.099	6.397
Number of Rooms	659	5.325	3.098	1	40
Number of Rooms (Log)	659	1.52	0.578	0	3.689
Stone floor (1,0)	659	0.777	0.417	0	1
Masonry wall (1,0)	659	0.915	0.279	0	1
Good roof (1,0)	659	0.948	0.221	0	1
Toilet with Septic Tank (1,0)	659	0.765	0.424	0	1
Spatial Characteristics					
Distance to Jakarta Center (km)	659	8.44	4.66	1.1	18.632
Distance to Jakarta Center (log)	659	1.958	0.624	0.096	2.925
High Educated HH	659	0.249	0.245	0.029	0.892
Flood Indicator					
Water Depth (cm)	659	43.371	24.605	0	115
Affected Area (RW)	659	0.035	0.032	0	0.273
Flood Recurrence	659	0.19	0.178	0	0.833
Period Inundation	659	0.093	0.093	0	0.425

Source: Author’s calculation from IFLS5, SUSENAS, OSM, LapakGIS, and BPBD

The minimum value in all four flood indicators is zero, meaning that the sub-district was not flooded in 2014. These areas were in Central Jakarta, which includes Menteng, Senen, and Gambir sub-district. In contrast, the most prone-flood areas were in East Jakarta, such as in Jatinegara and Kramat Jati sub-districts. The maximum value for the average water depth in 2014 was 115 cm, which occurred in Jatinegara, East Jakarta. Meanwhile, the maximum value for the average affected area RW-based is 0.273. This value belongs to the Pesanggrahan sub-district, meaning that, on average, 27.3 percent of RW in Pesanggrahan, or approximately 35600 households,

[5] These values and other extreme values are checked through housing websites in Jakarta to confirm if these are realistic numbers (see rumah.com; lamudi.co.id; rumah123.com).

[6] The house is located in Jatinegara, East Jakarta. Besides the very large house size value, the observation also does not have data on monthly house rent, which would make the observation not useful in the analysis.

was affected by the flood in 2014. The highest flood recurrence is at 0.833, or about 83 percent of the 12 months in 2014, equivalent with ten months, the sub-district was flooded at least once. Similarly, for the period of inundation, a value of 0.425 means that a sub-district was flooded 42.5 percent out of 365 days in 2014, or around 150 days. As mentioned previously, the period of inundation calculates the number of days the sub-district was flooded, while flood recurrence only counts the number of months the sub-district was flooded, regardless of the number of days. The different ways of calculating these two variables lead to different statistics, which would affect the impact on house rent presented in the later section.

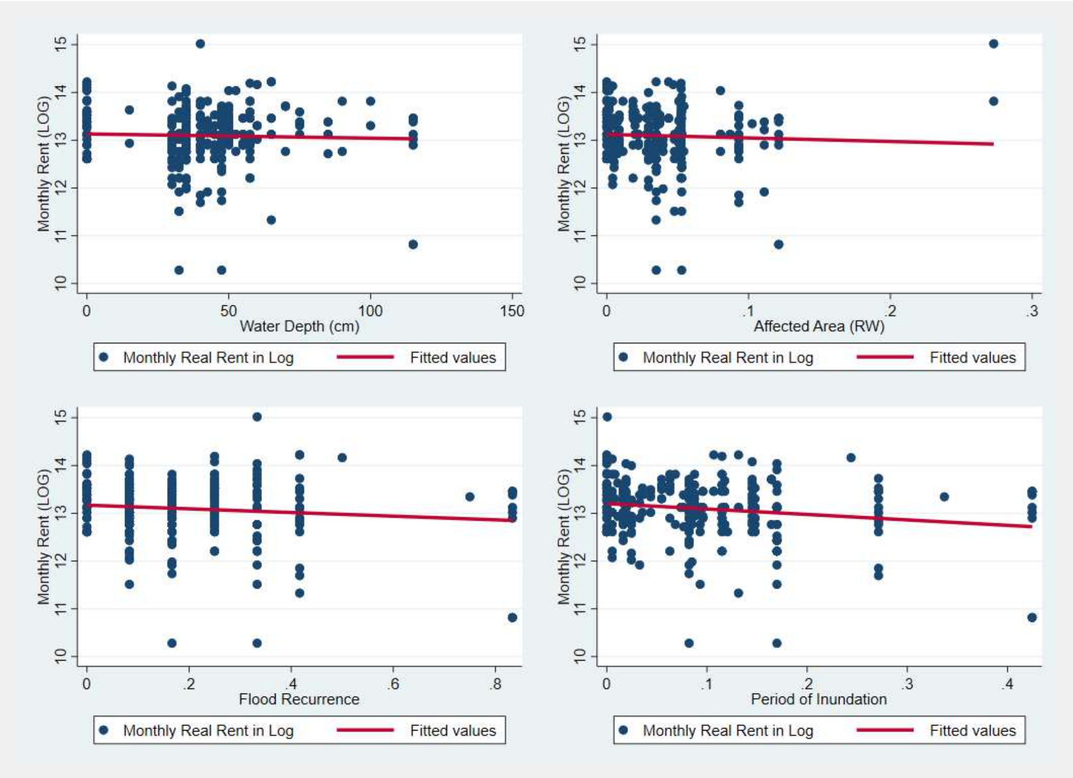
The pairwise correlations between real house rents and floods can be seen in Appendix A2. All flood indicators negatively correlate with the monthly house rent. The correlation is significant at 10 percent when looking at the flood recurrence, while it is significant at 1 percent if the indicator is changed into the period of inundation. An illustration of these four flood indicators' correlations with monthly house rent is depicted in the scatterplot in Figure 5. Appendix A2 also shows that all housing characteristics have a positive, strong correlation with house rent. The correlation between the number of rooms and house size is relatively high, at 0.67, statistically significant at 1 percent. This high correlation makes sense because usually, a large house would have more rooms; hence both variables will still be used in the analysis[7]. For the spatial characteristics, the distance to the center and the education variable have very weak correlations with house rent.

Similarly, the correlations between flood and WTP house rent can be seen in Appendix A3. The correlations with the housing characteristics remain highly significant. The area affected, flood recurrence, and the period of inundation are still negatively correlated with WTP rent. However, the flood recurrence indicator is no longer significant, while the affected area is significant at 10 percent level, and period of inundation is significant at 5 percent level. Interestingly, water depths are highly significant at 1 percent when using WTP Rent and positively correlated with house

[7] To prove that there are no multicollinearity problems between house size and the number of rooms, I tested all model specifications using either variable or both. The regression results are very similar, and the Variance Inflation Factor (VIF) in all results is always around 1.9-2.1, indicating a low correlation between house size and the number of rooms. Hence, including both variables in the models would not create a multicollinearity problem.

rent. The positive correlation indicates that larger and more expensive houses are located in sub-districts with high water depth. While referring to Figure 2, the data shows that sub-districts Setiabudi and Jatinegara have the highest average water depth at 100cm and 115cm, respectively. Meanwhile, the monthly WTP rent in these two areas can reach 35 million Rupiah per month or around 2300 US Dollars which is not too surprisingly as these two areas are known as business center since very long time ago[8]. Looking only at the correlations between WTP rent and water depth, it is evident that some expensive houses in Jakarta are in flood-prone areas. Appendix A4 shows these correlations between monthly WTP rent and four flood indicators as a scatterplot.

Figure 5. Correlations between Four Flood Indicators on Real Monthly House Rent



Source: Author's Calculation from IFLS5 and BPBD

[8] Jatinegara is one of the oldest areas in Jakarta and has become the center of economic activity for East Jakarta since the colonization period. The area was used for the military training center, a buffalo market, and as the vital transportation node connecting Jakarta and Bogor (Andi et al., 2021; The Jakarta Post, 2018). Meanwhile, Setiabudi was one of the first residential areas built after independence and was the business center for South Jakarta before moving further to the Sudirman area (Harahap, 2019).

4. Empirical Results

This section presents the results of the relationship between flood on monthly house rent in Jakarta in 2014 at the sub-district level. Table 2 presents the estimation results of the basic hedonic pricing model without any flood variables. Overall, using the real house rent explains the model better compared to when using the WTP rent. All housing characteristics are positively correlated with monthly rent and significant at least 5 percent level, except for having a toilet with a septic tank. The highest contribution comes from outer wall building material. Keeping everything else constant, a house with a masonry wall material has a higher house rent by 46.67 percent[9] compared to houses with lower quality wall material, statistically significant at 1 percent. As expected, the distance to the center negatively correlates with house rent, implying that people prefer to buy a house closer to the city center. The coefficient for highly educated households is positive and statistically significant at 10 percent, indicating that people like to live in a neighborhood with more high-educated households.

Table 2. Regression Results: Basic Hedonic Pricing Model

VARIABLES	Real Rent (Log)	WTP Rent (Log)
House size (log)	0.170***	0.200***
	(0.0599)	(0.0534)
Nr of Rooms (log)	0.235**	0.344***
	(0.0920)	(0.0858)
Toilet (1,0)	0.0232	0.291***
	(0.0793)	(0.0804)
Stone Floor (1,0)	0.227**	0.285***
	(0.0889)	(0.0630)
Masonry Wall (1,0)	0.383***	0.0346
	(0.110)	(0.0978)
Good Roof (1,0)	0.372**	0.0556
	(0.183)	(0.105)
Distance to center (log)	-0.265***	-0.332***
	(0.0709)	(0.0726)
High-educ HH	0.208*	-0.0732
	(0.120)	(0.107)
Constant	12.01***	12.60***
	(0.288)	(0.238)
Observations	284	656
R-squared	0.393	0.350

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

[9] The calculation for this magnitude is $(\exp^{0.383}-1)*100\% = 46.67\%$

Meanwhile, utilizing the WTP rent gives similar results to the real rent. Housing characteristics remain positively correlated with house rent, but only the coefficients of house size, number of rooms, toilet, and stone floor material are significant. Note that the toilet with a septic tank was previously insignificant when using the real rent. The toilet variable is a dummy equal to one for having a toilet with a septic tank. However, during the survey, respondents could choose other options, such as having a toilet without a septic tank or using public and communal toilets. It is likely that people, in reality, only value the availability of a toilet regardless of whether it has a septic tank, which makes the coefficient insignificant when using real rent. The distance to the center remains negative and significant, while the education coefficient is no longer significant. Based on the results in Table 2 and the higher R-squared when using real rent, the rest of this section will focus on real rent data instead of WTP Rent. Focusing on real rent will also avoid the tendency to overestimate house rent which often happens in willingness-to-pay scenarios. The results for WTP rent will be discussed as a robustness check in the later sub-section.

4.1 Flood Model

The main results of this study are presented in Table 3 below, showing the hedonic pricing model when including different flood indicators. Each of the four flood indicators is included in the model one by one to avoid multicollinearity. Like Table 2, all housing characteristics are positively correlated with house rent and statistically significant at 1 percent except for the toilet variable, in which the coefficient is insignificant. The distance to the center is negatively correlated with monthly rent and remains statistically significant at 1 percent, while the education variable is no longer significant. When including environmental amenities such as flooding, households may become indifferent to living near high-educated households. All flood indicators are negatively correlated with monthly house rent and statistically significant at 5 percent, except for the area affected.

The coefficients in Table 3 show the maximum point of impact if, for instance, the sub-district was flooded for the whole year in 2014. Referring to Table 1a in Section 3, the maximum value for the period of inundation in a sub-district is 0.425 or 155 days. This means that the maximum impact for the sub-district that was being inundated for 153 days would be a decrease of 44 percent[10] in the monthly house rent in that area, cateris paribus. Taking the average inundation period in Jakarta for 35 days, the impact of flooding on monthly rent is negative 12.27 percent[11]. Similarly, using flood recurrence as the flood indicator would indicate that within an average of 0.2 or equivalent with 2.5 months of flooding experience, the point impact for the sub-district would be a 12.7 percent[12] decrease in the monthly rent, cateris paribus. Both indicators showing the impact of flood frequency on monthly rent are similar to each other, suggesting that the impact is consistent and only differ in the way of calculating it.

Table 3. The Relationship between Flood and Monthly Rent

VARIABLES	Dependent Variable: Real Rent (log)			
	1	2	3	4
House Size (log)	0.185***	0.181***	0.189***	0.190***
	(0.0617)	(0.0630)	(0.0640)	(0.0628)
Nr of Rooms (log)	0.208**	0.228**	0.215**	0.211**
	(0.0907)	(0.0907)	(0.0875)	(0.0876)
Toilet (1,0)	0.0450	0.0204	0.0185	0.0173
	(0.0754)	(0.0790)	(0.0764)	(0.0763)
Stone Floor (1,0)	0.251***	0.232***	0.250***	0.257***
	(0.0900)	(0.0862)	(0.0855)	(0.0850)
Masonry Wall (1,0)	0.361***	0.370***	0.335***	0.333***
	(0.112)	(0.107)	(0.109)	(0.107)
Good Roof (1,0)	0.429**	0.397**	0.429**	0.415**
	(0.175)	(0.184)	(0.181)	(0.183)
Distance to Center (log)	-0.371***	-0.273***	-0.333***	-0.280***
	(0.0785)	(0.0702)	(0.0731)	(0.0700)
Highly-Educ HH	-0.198	0.136	-0.0375	-0.0273
	(0.193)	(0.125)	(0.141)	(0.126)
Water Depth (cm)	-0.00579**			
	(0.00266)			
Affected Area (RW)		-1.286		
		(1.458)		
Flood Recurrence			-0.679**	
			(0.330)	
Period of Inundation				-1.364**
				(0.540)
Constant	12.49***	12.05***	12.28***	12.17***
	(0.295)	(0.283)	(0.275)	(0.272)
Observations	284	284	284	284
R-squared	0.415	0.398	0.418	0.425

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

[10] The calculation for this magnitude is $(\exp^{0.425*(-1.364)} -1)*100\% = 44\%$
[11] The calculation for this magnitude is $(\exp^{0.096*(-1.364)} -1)*100\% = 12.27\%$
[12] The calculation for this magnitude is $(\exp^{0.2*(-0.679)} -1)*100\% = 12.7\%$

In the case of flood severity impact, water depth negatively impacts property values. A one-centimeter increase in the water depth is associated with a decrease in the monthly house rent by 0.58 percent, cateris paribus. Coming back to Figure 2, the highest average water level was in Setiabudi and Jatinegara. For these two sub-districts, the decrease in the monthly rent was between 55.68 percent and 66.7 percent. Meanwhile, utilizing the area affected as the flood indicator does not have a significant impact, possibly because this study aggregates the RW data into the sub-district level instead of directly analyzing at the RW level. Referring to Appendix A1, the RW level is actually a two-administration levels lower than the sub-district, hence, analyzing at the sub-district level may lead to imprecise estimates.

As indicated previously, estimating equation (1) may give biased estimates if there is unobserved heterogeneity affecting house rent from the variation between sub-districts. Table 4 investigates these potential variations through fixed effects analysis. The results show very similar coefficients with OLS regression estimations, in which using fixed effects slightly lower the coefficients. The distance to the center coefficient becomes much less significant in this model because the high house rent in properties near the national monument is now controlled through fixed effects. Although, the correlation is still negative, which is still as expected since the closer the house is to the center of Jakarta, the higher the monthly house rent. The education variable is still not significant but positively correlated with house rent.

Two flood indicators remain statistically significant in the fixed effect model. An increase of 10cm in the water depth decreases monthly house rent by 5.39 percent, statistically significant at 10 percent, cateris paribus. Within an average of 35 inundated days, flooding is associated with a decrease in the monthly rent by 10.44 percent[13], statistically significant at 5 percent, cateris paribus. The impact when using the period of inundation as the flood indicator decreases by two percent compared to the OLS estimation, which is very small. As the coefficients are similar to Table 4, the previous model has explained the model well, but using FE would still give more precise estimates. With FE, the flood recurrence is no longer significant because this indicator was calculated based on the number of months the sub-district was ever

[13] The calculation for this magnitude is $(\exp^{0.096*(-1.148)} - 1)*100\% = 10.44\%$

flooded, regardless of the number of days or the water depth. Controlling for the omitted factors across sub-districts lowers the explanatory power of flood recurrence.

Table 4. The Relationship between Flood and Monthly Rent (District Fixed Effects)

VARIABLES	Dependent Variable: Real Rent (log)			
	1	2	3	4
House Size (log)	0.172***	0.174***	0.182***	0.187***
	(0.0619)	(0.0658)	(0.0662)	(0.0655)
Nr of Rooms (log)	0.206**	0.220**	0.211**	0.207**
	(0.0901)	(0.0896)	(0.0877)	(0.0871)
Toilet (1,0)	0.0109	-0.00376	-0.00231	-0.00109
	(0.0771)	(0.0788)	(0.0767)	(0.0762)
Stone Floor (1,0)	0.245***	0.233***	0.247***	0.257***
	(0.0855)	(0.0841)	(0.0826)	(0.0818)
Masonry Wall (1,0)	0.344***	0.361***	0.333***	0.326***
	(0.111)	(0.109)	(0.108)	(0.106)
Good Roof (1,0)	0.485***	0.449**	0.470***	0.461***
	(0.169)	(0.178)	(0.176)	(0.178)
Distance to Center (log)	-0.209**	-0.102	-0.177*	-0.147
	(0.0987)	(0.0977)	(0.0952)	(0.0952)
Highly-Educ HH	0.0965	0.427	0.211	0.137
	(0.339)	(0.299)	(0.304)	(0.308)
Water Depth (cm)	-0.00539*			
	(0.00299)			
Affected Area (RW)		-0.618		
		(1.363)		
Flood Recurrence			-0.519	
			(0.328)	
Period of Inundation				-1.148**
				(0.532)
Constant	12.31***	11.78***	12.02***	11.94***
	(0.330)	(0.303)	(0.281)	(0.286)
Observations	284	284	284	284
R-squared	0.435	0.421	0.433	0.441
District FE	YES	YES	YES	YES

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.2 Robustness Check

As a robustness check, this study utilizes the monthly WTP rent data to look at the impact of floods on Jakarta's property values. The results when using OLS regression can be seen in Appendix A5. Compared to Table 3, the coefficients are relatively higher, and all flood indicators are negatively correlated with monthly WTP rent and statistically significant by at least 10 percent, except for water depth. Table 6 presents the regression results utilizing the WTP rent with district-fixed effects. The coefficients are relatively similar to the real rent data in Table 5, but some signs and significance levels differ. The coefficient signs and statistical significance of housing characteristics do not change from the basic hedonic model estimations in Table 2. Adding the flood variables does not change the significance level for the wall and roof material variables, which remain insignificantly correlated with house rent.

Focusing on the comparison between Table 5 and 6, the distance to the center remains negatively correlated with house rent. However, unlike in the real rent data, the variable is insignificant only when using water depth as the flood indicator in the WTP rent data. On top of utilizing the fixed effect in the model, one possible reason is that the correlation between water depth and the distance to the center is pretty high. Based on the pairwise correlation in Appendix A3, the correlation between these two variables is 0.518, while it is less than 0.5 for all other flood indicators. As for the education variable, same as in the rent data, the household education variable remains insignificant in Table 5.

The flood recurrence and period of inundation are negatively correlated with monthly WTP rent, statistically significant at 10 percent and 5 percent, respectively. On average, flood recurrence decreases the monthly WTP rent by 7.12 percent[14], cateris paribus. Meanwhile, being inundated for an average of 34 days decreased the monthly WTP rent by 7.2 percent[15], cateris paribus. Comparing to the results of real rent data in Table 4, both estimates become lower, indicating that people may underestimate the flood impacts in valuing properties and put more value on the housing characteristics instead.

The flood severity indicators are not statistically significantly correlated with monthly WTP rent. The area affected is negative and insignificant, the same as in Table 5, while water depth becomes positive and insignificant. In Appendix A3, the water depth has a positive and significant correlation with monthly WTP rent if we do not include any other variables. However, controlling for other variables makes the water depth no longer significant, as housing characteristics can explain the model better. From this robustness check, utilizing the period of inundation gives the most consistent results. The variable is always negatively and significantly correlated with monthly rent throughout different specifications. For the rest of the variables, although

[14] The calculation for this magnitude is $(\exp^{0.19*(-0.388)} -1)*100\% = 7.12\%$
[15] The calculation for this magnitude is $(\exp^{0.093*(-0.804)} -1)*100\% = 7.2\%$

some of the coefficients may differ compared to the real rent data, the overall results in the WTP rent still show relatively similar coefficients.

Table 6. Robustness Check: The Relationship between Flood and Monthly WTP Rent (District Fixed Effects)

VARIABLES	Dependent Variable: WTP Rent (log)			
	1	2	3	4
House Size (log)	0.198***	0.196***	0.194***	0.193***
	(0.0541)	(0.0545)	(0.0545)	(0.0545)
Nr of Rooms (log)	0.350***	0.348***	0.344***	0.345***
	(0.0873)	(0.0872)	(0.0869)	(0.0872)
Toilet (1,0)	0.265***	0.265***	0.258***	0.256***
	(0.0820)	(0.0822)	(0.0824)	(0.0826)
Stone Floor (1,0)	0.282***	0.275***	0.266***	0.266***
	(0.0633)	(0.0629)	(0.0633)	(0.0634)
Masonry Wall (1,0)	0.0446	0.0523	0.0497	0.0619
	(0.0996)	(0.100)	(0.100)	(0.100)
Good Roof (1,0)	0.0749	0.0743	0.0850	0.0781
	(0.106)	(0.104)	(0.103)	(0.102)
Distance to Center (log)	-0.158	-0.222**	-0.263**	-0.232**
	(0.101)	(0.106)	(0.108)	(0.103)
Highly-Educ HH	0.212	0.0271	-0.101	-0.149
	(0.250)	(0.229)	(0.244)	(0.247)
Water Depth (cm)	0.00187			
	(0.00213)			
Affected Area (RW)		-1.140		
		(0.927)		
Flood Recurrence			-0.388*	
			(0.208)	
Period of Inundation				-0.804**
				(0.374)
Constant	12.22***	12.52***	12.70***	12.63***
	(0.306)	(0.279)	(0.305)	(0.276)
Observations	656	656	656	656
R-squared	0.356	0.357	0.360	0.361
District FE	YES	YES	YES	YES

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

5. Discussions

This section discusses the results by looking back to the literatures and the limitations of this study. Throughout all specifications, housing characteristics positively correlate with monthly rent. House size, number of rooms, toilet with a septic tank, and good building materials give positive values to the monthly house rent, consistent with previous literature (Cobian & Resosudarmo, 2019; Yusuf & Koundouri, 2005; Yusuf & Resosudarmo, 2009). The distance to the center of Jakarta is consistently negatively associated with monthly rent, as suggested by previous studies (Glaeser &

Kahn, 2003; Yusuf & Koundouri, 2005). However, the significance of this distance variable is reduced when controlling the variation between sub-districts through Fixed Effect. Yusuf and Resosudarmo (2009) suggest a better measure for the distance variable would be the distance to the center of each district instead of the national monument. As Jakarta is a big city with high density, each district has its business center where people want to live nearby (Yusuf & Resosudarmo, 2009). Meanwhile, this study has yet to find a significant relationship between living around high-educated households and house rent. Cobian and Resosudarmo (2019) and Yusuf and Resosudarmo (2009) previously found a significant positive correlation between education and monthly rent only after controlling for spatial dependence.

The main interest of this study is to look at the impact of flooding on property values in Jakarta. First, focusing on the severity of the flood, the estimates in this study for water depth are found to be five times higher compared to a similar study by Cobian and Resosudarmo (2019). Even though their study investigated the impact of Jakarta's flood in 2007, their estimates show a decrease in the monthly house rent by 0.124 percent for a 1 percent higher flood water level. Ortega and Taspinar's (2018) findings were also around 11 to 17 percentage points, much lower than this study's findings. However, high estimates are expected because Cobian and Resosudarmo (2019) controlled for the spatial dependence using the spatial lag model, while Ortega and Taspinar (2018) used the exact flood water level data on each point to get more precise estimates.

Another way to investigate the impact of flood severity on house rent is by investigating the affected area from the flooding. This study measures damaged properties by the average number of RW affected by the flood in a sub-district. The results with this indicator mostly show insignificant results, although consistently negative. One problem in using the affected area is that there was no information on the damage level for each affected household. Ortega and Taspinar (2018) found a significant decrease of 17 percent to 22 percent in house prices for damaged properties using detailed aerial imagery provided by the government.

Moving on to the impact of flooding on property values based on the flood frequency, the results show more sound estimates. Using flood recurrence, or the fraction of months the sub-district was flooded in 2014, the results are consistent with previous findings that found higher impacts for higher flood frequency (Beltrán et al., 2019; Lamond et al., 2010; Tobin & Newton, 1986). The estimates in this study are not far different from Lamond et al. (2010), who found slightly lower estimates. However, compared to the results found by Hirsh and Hahn (2018), the finding in this study remains higher. Although tenants do not have to cover financial damage from flooding, there are still uninsured household goods tenants are responsible for, and landlords may pass the flood damage to the rental price (Hirsh & Hahn, 2018). Therefore, Jakarta's landlords tend to incorporate higher potential damages from flooding since flooding in Jakarta is more common than in Germany.

The last flood indicator evaluated in this study is the period of inundation or the fraction of the number of days the sub-district was inundated by flood. Throughout all specifications, using the inundation period gives highly significant and negative correlations with monthly rent. The results are also robust when checked with the monthly WTP rent. Taking the maximum impact of period of inundation on monthly rent, this study's estimates are comparable with Atreya and Ferreira's (2015) findings. This study also confirms Beltrán et al. (2019) finding that the longer the period of inundation, the higher the impact of flooding on property values. Capturing the impact of flooding for inundated properties captures the costs of potential uninsurable reconstruction and psychological damages carried by the renters (Atreya & Ferreira, 2015; Tversky & Kahneman, 1973). The period of inundation is also a reliable indicator as it is calculated based on the number of days, creating more precise results.

5.1 Flooding and House Price in Jakarta

The results of this study confirm the correlations between flood severity and flood frequency with the very high house price in Jakarta. Sub-districts in East Jakarta, such as Jatinegara and Kramat Jati, has a very high flood frequency and high-water depth, but the house price in these two sub-districts can reach six million Rupiah or around 400 US Dollar per month. In more extreme cases, Pasar Minggu, Pesanggrahan, Kebayoran Baru, and other sub-districts in South Jakarta are relatively prone to flood, but monthly house rent may reach 25 million Rupiah or around 1700 US Dollars per month.

Three reasons can explain this striking fact. First, based on the estimates presented in this study, people tend to put more value on housing characteristics compared to flooding in renting a house. In all specifications, the housing characteristics estimates are relatively higher than the flood estimates and even higher when looking at the monthly WTP rent. People know most parts of Jakarta are prone to flood; hence they may underestimate the impact of flooding and focuses on, for instance, the building materials of the house.

Second, many of these flood-prone sub-districts are the center of economic activities, creating the demand to live in these areas very high. Jatinegara, Kebayoran Baru, and Pasar Minggu are all areas with economic business centers where people come and do their daily economic activities. Moving to other parts of Jakarta with much less flooding, such as Penjaringan or Sawah Besar sub-districts, is undesirable because the economic activities in these areas are lower. Hence, the opportunity cost to move to a less flood-prone area is higher than the cost to cover the flood damage from living in a high flood-risk area. This high housing demand leads to the subsequent reasoning i.e., landlords can charge higher rent to the renters. The potential damages from flooding that the landlords are responsible for are passed into the monthly rent of the house. The higher the expected flood impact in the area, the higher the value landlords will charge to the house rent, increasing the monthly rent in flood-prone areas further.

5.2 Study Limitations

There are two main concerns regarding the quality of the estimations. First, the quality and availability of data. Instead of using housing transaction data, this study uses monthly rent as a proxy of house price. Transaction data on Jakarta's housing is difficult to obtain since it is not publicly available and sometimes needs to be calculated manually from the building tax. The aggregation for the spatial characteristics and flooding data into the sub-district level also makes the estimates imprecise compared to utilizing data at the lowest possible administration level, i.e., household level. Although, analyzing the result at the sub-district level remains relatively credible since flooding in a village will most likely affect another village, and floods are usually managed at the sub-district level (Cobian & Resosudarmo, 2019). The flood data could also be improved since the water level data in this study is taken as an average of the minimum and maximum water levels. Using more precise flood data, such as point water level data, would give more precise estimates (Ortega

& Taspinar, 2018). This measurement issue also supports the inconsistent results for water depth in this study in some specifications.

Second, this study uses OLS and fixed effects as the methodology for analyzing the impact of flooding on property values. Although utilizing fixed effects helps eliminate the risk of a bias due to omitted factors that vary across sub-districts, the coefficients are still large compared to other studies. There are likely other omitted variables that are not controlled and create a bias, such as the clustering of high-income people in a sub-district. Furthermore, since the size of a sub-district in Jakarta is pretty large (refer to Figure 3 in Section 3), flooding in neighboring sub-districts likely affects the house rent in a sub-district (Yusuf & Resosudarmo, 2009).

6. Conclusion

This study measures the impact of flooding on property values in Jakarta, Indonesia, using the hedonic pricing approach. The analysis is performed by looking at the monthly house rent at the sub-district level in 2014 with four types of flood indicators. The average water depth and area affected based on the RW level (lower administration level) represents flood severity, while the flood recurrence and period of inundation are proxies for flood frequency. In all flood indicators, this study confirms that flooding impacts property values in Jakarta negatively. The period of inundation gives the most consistent results compared to the similar studies in other countries.

Policymakers can take away two main implications. The government should provide housing alternatives in non-flooded areas with high economic activity. Otherwise, people will prefer to stay at their current home since the opportunity cost to move is higher than the damage from flooding. Two, in order to lower the monthly house rent in Jakarta, the government should invest in providing better infrastructures to prevent flooding. By keeping underground aquifers and floodgates in good maintenance, clean canals, and efficient draining systems, the potential damage from flooding that landlords incorporate into the monthly rent will decrease; hence the rent paid by renters. This study motivates future research to focus on how people making decision to stay at the flooding area or move. Further, to overcome the limitation of this study, the spatial dependence method should be applied in Jakarta to obtain more precise estimates.

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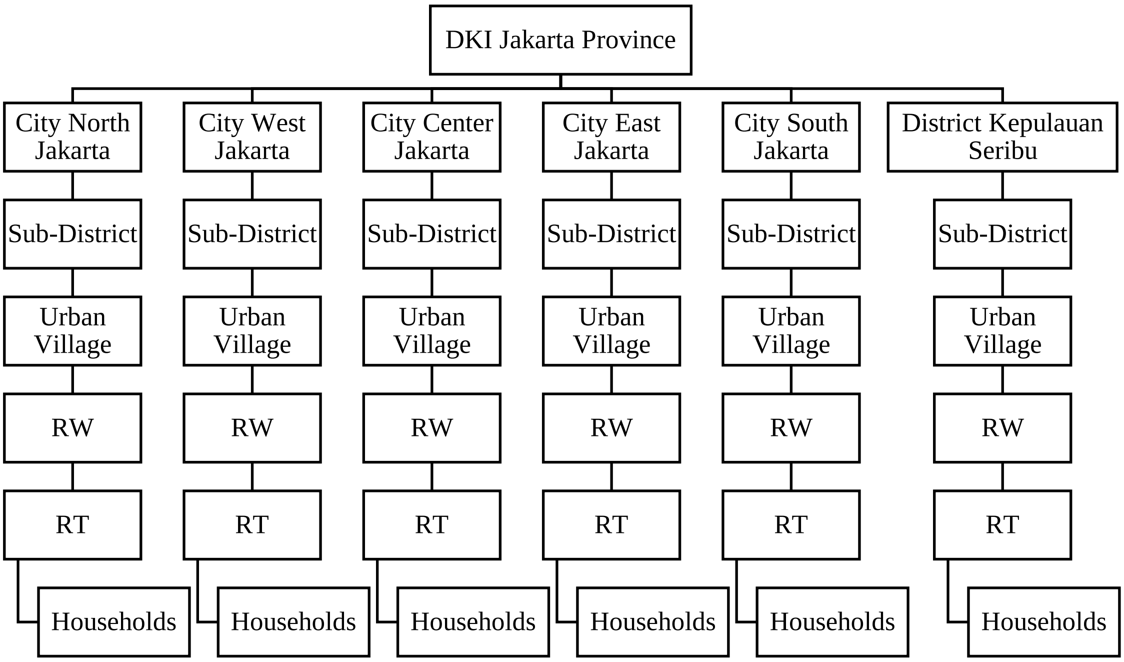
Appendices

Appendix A1. Administration Hierarchy for DKI Jakarta



Source: Own Illustration according to Law No.32/2004 concerning Regional Administration. Note: Based on Law No.22/2004 on RW and RT and the Central Bureau of Statistics, a city consists of 6 to 10 sub-districts on average, while a sub-district has around 7 urban villages. An urban village generally has 10 RW, and each RW manages no more than 16 RT. The lowest administration level, RT, consists of a maximum of 160 households within one RT.

Appendix A2. Pairwise correlations: Real Rent

Variables	Real rent (log)	House size (log)	Nr of rooms (log)	Toilet with septic tank	Stone floor	Masonry wall	Good roof	Distance to center (log)	High-educ HH	Flood Recurrence	Affected Area (RW)	Period of Inundation	Water Depth
Real rent (log)	1.000												
House size (log)	0.416***	1.000											
Nr of rooms (log)	0.396***	0.677***	1.000										
Toilet with septic tank (1,0)	0.324***	0.419***	0.467***	1.000									
Stone floor (1,0)	0.375***	0.227***	0.175***	0.298***	1.000								
Masonry wall (1,0)	0.405***	0.198***	0.166***	0.331***	0.528***	1.000							
Good roof (1,0)	0.156***	0.079	0.111*	0.074	0.115*	0.028	1.000						
Distance to center (log)	-0.051	0.266***	0.235***	0.160***	0.136**	0.057	0.075	1.000					
High-educ HH	0.068	-0.160***	-0.123**	-0.066	-0.020	-0.040	-0.090	-0.713***	1.000				
Water Depth (cm)	-0.034	0.150**	0.040	0.113*	0.085	0.069	0.124**	0.483***	-0.617***	1.000			
Affected Area (RW)	-0.044	0.160***	0.051	0.020	0.032	-0.047	0.128**	0.290***	-0.364***	0.381***	1.000		
Flood Recurrence	-0.106*	0.114*	0.002	0.004	0.030	-0.065	0.122**	0.317***	-0.434***	0.695***	0.720***	1.000	
Period of Inundation	-0.174***	0.111*	0.001	0.003	0.051	-0.082	0.104*	0.323***	-0.439***	0.557***	0.666***	0.902***	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Source: Author's calculation from IFLS5, SUSENAS, OSM, LapakGIS, and BPBD

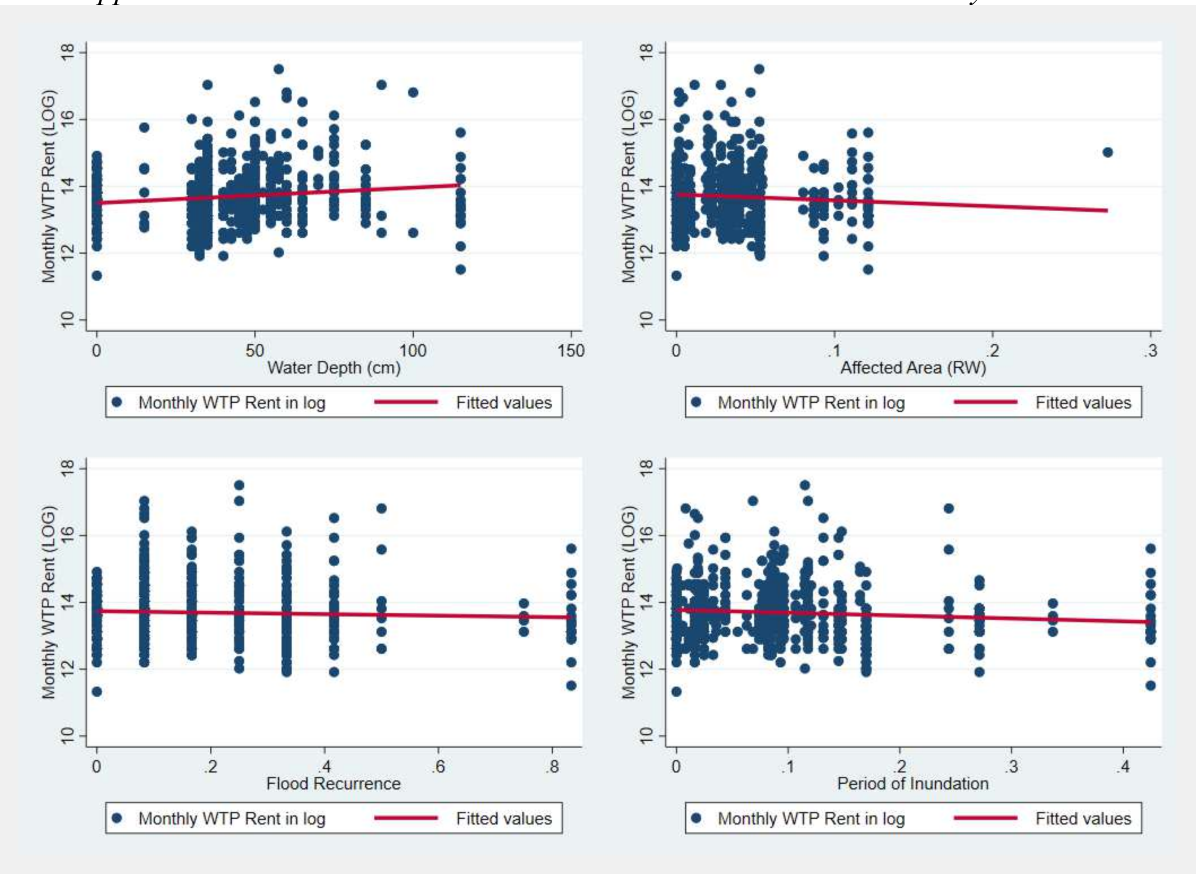
Appendix A3. Pairwise correlations: WTP Rent

Variables	WTP rent (log)	House size (log)	Nr of rooms (log)	Toilet with septic tank	Stone floor	Masonry wall	Good roof	Distance to center (log)	High-educ HH	Flood Recurrence	Affected Area (RW)	Period of Inundation	Water Depth
WTP rent (log)	1.000												
House size (log)	0.488***	1.000											
Nr of rooms (log)	0.493***	0.735***	1.000										
Toilet with septic tank (1,0)	0.320***	0.333***	0.338***	1.000									
Stone floor (1,0)	0.302***	0.262***	0.255***	0.287***	1.000								
Masonry wall (1,0)	0.259***	0.288***	0.264***	0.357***	0.399***	1.000							
Good roof (1,0)	0.099**	0.132***	0.139***	0.146***	0.155***	0.150***	1.000						
Distance to center (log)	0.039	0.178***	0.114***	0.296***	0.147***	0.053	0.117***	1.000					
High-educ HH	-0.090**	-0.170***	-0.114***	-0.292***	-0.132***	-0.088**	-0.126***	-0.696***	1.000				
Water Depth (cm)	0.134***	0.136***	0.073*	0.187***	0.086**	0.110***	0.079**	0.518***	-0.662***	1.000			
Affected Area (RW)	-0.068*	0.000	-0.008	0.034	-0.006	0.022	0.032	0.295***	-0.342***	0.415***	1.000		
Flood Recurrence	-0.047	0.001	-0.027	0.014	-0.041	0.009	0.037	0.319***	-0.415***	0.709***	0.731***	1.000	
Period of Inundation	-0.093**	-0.010	-0.024	0.032	-0.025	0.031	0.042	0.333***	-0.434***	0.587***	0.743***	0.907***	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Source: Author's calculation from IFLS5, SUSENAS, OSM, LapakGIS, and BPBD

Appendix A4. Correlations between Four Flood Indicators on Monthly WTP Rent



Source: Author's Calculation from IFLS5 and BPBD

Appendix A5. The Relationship between Flood and Monthly WTP Rent

VARIABLES	Dependent Variable: WTP Rent (log)			
	1	2	3	4
House Size (log)	0.200***	0.198***	0.197***	0.195***
	(0.0534)	(0.0536)	(0.0537)	(0.0537)
Nr of Rooms (log)	0.346***	0.344***	0.339***	0.343***
	(0.0863)	(0.0862)	(0.0858)	(0.0861)
Toilet (1,0)	0.291***	0.283***	0.278***	0.274***
	(0.0805)	(0.0806)	(0.0806)	(0.0810)
Stone Floor (1,0)	0.286***	0.280***	0.271***	0.271***
	(0.0633)	(0.0632)	(0.0636)	(0.0637)
Masonry Wall (1,0)	0.0328	0.0432	0.0389	0.0537
	(0.0978)	(0.0973)	(0.0972)	(0.0979)
Good Roof (1,0)	0.0536	0.0553	0.0671	0.0592
	(0.106)	(0.105)	(0.103)	(0.101)
Distance to Center (log)	-0.320***	-0.330***	-0.375***	-0.339***
	(0.0710)	(0.0727)	(0.0743)	(0.0725)
Highly-Educ HH	-0.0165	-0.152	-0.248*	-0.242*
	(0.163)	(0.114)	(0.129)	(0.124)
Water Depth (cm)	0.000746			
	(0.00190)			
Affected Area (RW)		-1.641*		
		(0.840)		
Flood Recurrence			-0.452**	
			(0.198)	
Period of Inundation				-0.920**
				(0.365)
Constant	12.53***	12.68***	12.85***	12.77***
	(0.255)	(0.242)	(0.263)	(0.245)
Observations	656	656	656	656
R-squared	0.350	0.353	0.357	0.358

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1