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RESEARCH ARTICLE

The cost of floods in developing countries' megacities: a hedonic price analysis of the Jakarta housing market, Indonesia

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Abstract

Although many megacities in developing countries experience floods annually that affect a large number of people, relatively few empirical studies have evaluated the associated costs. This paper estimates such costs by conducting a hedonic price analysis—providing evidence regarding the impacts of floods on the housing market. A robust regression technique on a simple linear transformation model, and a maximum likelihood estimation technique on the spatial lag version of the simple linear transformation model, are utilised to estimate the correlation between the level of the 2007 floods and monthly housing rental prices in Jakarta, Indonesia. This paper sheds light on the fact that in developing countries' megacities, the total cost of floods among households is significantly lower compared to the total amount of funding needed to permanently eliminate floods in these megacities. Hence, a constant exposure of the urban areas in developing countries to flood damage will most likely keep happening.

Keywords Environmental economics · Hedonic price analysis · Spatial analysis · Flood

JEL classification Q51 · Q54 · R32 · O21

1 Introduction

Climate change is causing an increase in extreme weather and climate events, especially in developing countries. These countries are more vulnerable due to their geographic exposure, poverty, high dependence on agriculture, rapid population growth and limited capacity to cope with an uncertain climate. This leads to increased

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human exposure to natural disasters such as heatwaves, droughts, storms and floods, which are becoming more frequent as the world gets warmer (Stern 2007). Among these major weather events, floods have been recognised as a major cause of economic damage worldwide which, in turn, affects a large number of people (UNISDR 2002). More specifically, this phenomenon has become an annual event over the past few decades in many developing countries' megacities, and has heavily impacted Asia, where there are large concentrations of people in urban areas (World Resources Institute 2015).

In 2014, the level of urbanisation in developing countries was approximately 48.4%, and in the Asian region, the proportion of people living in urban areas was approximately 47.5% (UN 2014). Urbanisation in developing countries has brought on urban management challenges related to the lack of physical infrastructure and inadequate urban services (Cohen 2004). In some cities, urban expansion has been unplanned or inadequately managed, leading to rapid sprawl, pollution, and environmental degradation, accompanied by unsustainable production and consumption patterns (UN 2014).

An apparent lack of capability in managing urban development, as a result of high rates of urbanisation and large populations, along with increasing climate variability and rising sea levels are typically suspected as the main causes of these floods. It is not uncommon that these floods annually cause serious natural disaster events in developing countries (UN and WB 2010). A study undertaken by the World Resources Institute (2015) considered Indonesia to be one of the countries with the greatest number of people exposed to flood risk, ranking 6th out of 164 countries in 2010. Jakarta comprises the largest urban area in Indonesia with a population density of approximately 14, 000 people per km^2 (Yusuf et al. 2009).

In Jakarta, the cause of flooding is due to not only increasing climate variability and rising sea levels, but also the extensive use of ground water, which has caused subsidence in several areas (World Bank 2011). Flooding is an annual disaster event in Jakarta and most of the time affects a significant number of residents in the city. However, nearly every 5 years when the El Niño phenomenon occurs, the city experiences considerable floods. For example, the 2007 floods were one of the most significant, inundating almost 36% of Jakarta city, in some areas to a depth of seven metres, resulting in over 70 deaths and 340,000 displaced people (Jha et al. 2012; Budiyono et al. 2016). In 2012 and 2017, Jakarta was again hit by considerable flood events.

Due to growing concern over the impact of floods on Jakarta, local government and non-government organisations have been developing several intervention programmes, including better managing the risk of disaster, and the resettlement of urban poor populations at the lower end of the scale, up to reducing greenhouse gas emissions (Baker 2011). Several of these activities are as follows. Since 2012, with World Bank support, the Jakarta government has developed projects under the "Jakarta Urgent Flood Mitigation Project" to dredge a number of vital floodways and retention basins, and rehabilitating embankments and mechanical equipment that are part of Jakarta's flood management system. This project aims to keep Indonesia's capital safer from floods with an investment of USD 139.6 million or Rp 2.5 trillion (World Bank 2016).

However, some constraints have proved to be an obstacle to the success of these initiatives, such as the much-needed upgrades to the city infrastructure, the significant lack of research and data regarding floods to support decision making, and the absence of community engagement—both government and community—to take necessary action. The cost of the projects needed to mitigate floods in Jakarta is also not trivial. The Jakarta Water Management Agency estimated that the city needs Rp. 118 trillion (USD 9.2 billion)—approximately twice the total revenue of Jakarta government in 2015—to comprehensively mitigate the seasonal flooding in Jakarta (Tambun et al. 2015). Therefore, reducing the flood risk in Jakarta still remains a challenge to be tackled by the Indonesian government, as a key priority within disaster management.

As has been mentioned already, although flooding is a significant occurrence for consideration by any government in developing countries, there has been little research and limited evidence of evaluating the cost to their megacities. Most research has focused on flood risk in developed countries, particularly the United States of America (USA), and has studied the impact of flooding on the price differential of property values and their relation to insurance costs (Carbone et al. 2006; Bin and Landry 2013; Bin and Polasky 2004; Bin et al. 2008a; Atreya et al. 2013).

Until recently, only a few studies have analysed the economic damage and loss due to flooding, none of which demonstrate clear patterns in the annual damage costs caused by flooding. On one hand, Budiyono et al. (2015) identified areas of highest risk and assessed Jakarta's risk using the damage scanner model. They found the annual expected damage due to river flooding in Jakarta to be approximately US$ 321 million per year, and obtained new estimates of economic exposure values for different land use classes (industry and warehouse, commercial and business, planned house, and density urban). While the study undertaken by Wijayanti et al. (2017) measured flood damage in Jakarta but distinguished between residential and business sectors, with reported values of US$ 1.3 million and US$ 9.2 million in 2013, respectively. Lastly, Wahab and Tiong (2017) make reference to the National Development Planning Agency's formal estimates for direct flood damage in 2002 and 2007 floods as being Rp 5.4 trillion and Rp 5.2 trillion, respectively (Bappenas 2007, cited in Wahab and Tiong 2017). This is in the context of their proposed multi-variate residential flood loss estimation model to estimate direct tangible loss to buildings and contents for the residential sector after the 2013 January floods. The results show that as water flood level (expressed in water depth) increases, the building structure and contents losses (expressed in terms of US$) tend to rise, but the tangible loss for the residential sector in Jakarta city is greater in higher, rather than lower, income areas.

In an attempt to fill the recognised research gap, this paper will apply a technique known as hedonic property value analysis (see "Appendix A" for more information on this method), using a combination of data obtained from the Indonesian Family Life Survey (IFLS), and flood-level data in Jakarta obtained from the United Nations Department of Safety and Security (UNDSS).

This paper will apply the hedonic price method to see whether the annual flood events have an impact on the housing values[1] in Jakarta, Indonesia. Since this is an annual event, though the size might vary annually, we can expect the housing rental market to be in its equilibrium condition. This study differs from the findings of previous papers, because we study an annual event of flood, as opposed to random flooding events. The main objective is to analyse whether the annual flood events are directly correlated with property values in Jakarta.

The paper is divided into six sections, the background and motivation for the research; the use of the hedonic property value method in previous studies; the study area and data utilised in the paper; the empirical modelling; the results obtained from the data; and the concluding statements.

2 Literature review

Flooding is also considered as an attribute that may affect the willingness to pay for the house; therefore, the structure of housing rents and prices would reflect these differentials. Using data on rent of different properties, the hedonic price analysis can identify the impact of flood events on the value of the house. This determines an implicit or shadow price of this attribute that can be used to calculate the willingness to pay for the non-marketed goods, namely the perception of flood risk. The method used to implement this approach is the hedonic technique pioneered by Lancaster (1966) and formalised by Rosen (1974).

This technique has been widely utilised in environmental economics literature to estimate the price difference between residential properties located within or outside floodplain regions. Some of them can be seen in Table 1. Most of these studies demonstrate a negative relation between the housing prices and flood events, whereby the properties located in the floodplain are likely to be impacted by a price decrease, in comparison to those properties located in non-floodplain areas. Further to this, following a flood phenomenon, owners of houses located in floodplain areas are forced to pay an increased insurance premium. Skantz and Strickland (1987) note that house price reactions to flood events initially declined and later regained their lost value due to the market forgetting about the flood event.

Using a semi-logarithmic functional form for hedonic property value analysis, they found there was no immediate decline in flooded home prices after the flood event. This was due to the flood insurance premium being subsidised by the federal government. A year later, when the government cut the economic support, floodplain houses experienced a decrease in property values.

[1] Value measured as a monthly rate—represented as dependent variable monthly rent—is based on potential and actual rental prices. This considers the fact that 70% of observations represent owner-occupied homes with no set rental price, therefore it is considered as a potential rental price only [asked as "Rent would pay per month" (IFLS 2007)]. The other 30% are renter-occupied homes with an actual rental price.

Table 1 Summary of existing hedonic price studies related to flood events

No	Author (publication year)	Method	Location	Results
1	Skantz and Strickland (1987)	OLS and event study hedonic	TX, USA	Negative; not significant
2	Bin and Polasky (2004)	D–D hedonic	NC, USA	− 5.7%; significant
3	Carbone et al. (2006)	D–D hedonic	FL, USA	− 20% to − 30%; significant
4	Daniel et al. (2007)	OLS and spatial hedonic	Netherlands	− 7% to − 13%; significant
5	Bin et al. (2008a)	Spatial hedonic	NC, USA	− 11%; significant
6	Bin et al. (2008b)	Spatial hedonic	NC, USA	− 7.3%; significant
7	Pope (2008)	Spatial FE hedonic	NC, USA	− 4%; significant
8	Samarasinghe and Sharp (2010)	Spatial hedonic	New Zealand	− 6.2%; significant
9	Kousky (2010)	D–D hedonic	MI, USA	− 2.6%; significant
10	Bin and Landry (2013)	D–D hedonic	NC, USA	− 5.7% and − 8.8%; significant
11	Kousky and Walls (2014)	Simulation	MI, USA	− 0.7%; not significant
12	Rabassa and Zoloa (2016)	OLS and spatial hedonic	Buenos Aires, Argentina	− 17.3%; significant

Ordinary least square (OLS) and difference-in difference (D–D)

Bin and Polasky (2004) also utilised the hedonic property price function to estimate the flood hazard effects on property values in Pitt County, North Carolina. The methodology used an OLS regression analysis which found that after Hurricane Floyd in 1999, houses located in a floodplain were impacted by a price discount. The marginal effect estimated for the property values located in the floodplain was approximately $ 7463, i.e., the property value in the floodplain was lowered by that amount of money.

This formed the basis for the study undertaken by Bin and Landry (2013), which re-examined and compared findings with a previous flooding event regarding lessee preferences in a market clearing equilibrium condition—1996 Hurricane Fran—using difference-in-difference (DID) and spatial effect models (spatial lag and spatial error). They found that average real property values decreased by approximately 5.7% after Hurricane Fran compared to approximately 8.8% after Hurricane Floyd; however, in between both hurricanes, they increased by approximately 2.2%. This price increase is due to the lessee becoming more insensitive to flooding events, since the perception of flood risks and cost associated with it are not persistent over time.

Most of the published literature analysing the relationships between floods and hedonic property value concerns the USA (Table 1). There are some studies regarding other developed countries, such as the Netherlands (Daniel et al. 2007) and New Zealand (Samarasinghe and Sharp 2010); and very few on developing countries. Among the few is a study by Rabassa and Zoloa (2016) which attempts to determine whether flood events are associated with property values in La Plata city, Argentina. Using data from land parcel sales in 2004, they found that property sale prices were affected by a discount of approximately 17.3% for properties located in flood-prone areas, as opposed to those situated outside of the floodplain.

Another important characteristic regarding the most recent studies is their coverage of flood events not occurring on an annual basis. Floods in the southern part of the USA might happen frequently, but only once every few years, so that the prices immediately following the shock may not yet be equilibrium prices. In this sense, floods in Jakarta differ from the floods in the southern part of the USA. As mentioned before, floods are an annual disaster event in Jakarta and nearly every 5 years, when the El Niño Phenomenon occurs, the city experiences considerable flooding. Housing prices observed in this study are mostly equilibrium prices.

3 Study area and data sources

The city of Jakarta, the capital of Indonesia, is the study area of this paper. Jakarta has been one of the fastest-growing megacities in the world. Approximately, 6.5 million people resided in this city in 1980 compared to more than 10 million people in 2016 (CEIC 2017). The city lies on a low, flat alluvial plain formed by the mouth of the Ciliwung River (the main river) where it meets Jakarta Bay. This river travels through the middle of the city and divides it into western and eastern areas. The Pesanggrahan and Sunter are less turbulent rivers and cross the western part of Jakarta. Thus, most of the city is prone to swampy and flooded conditions,

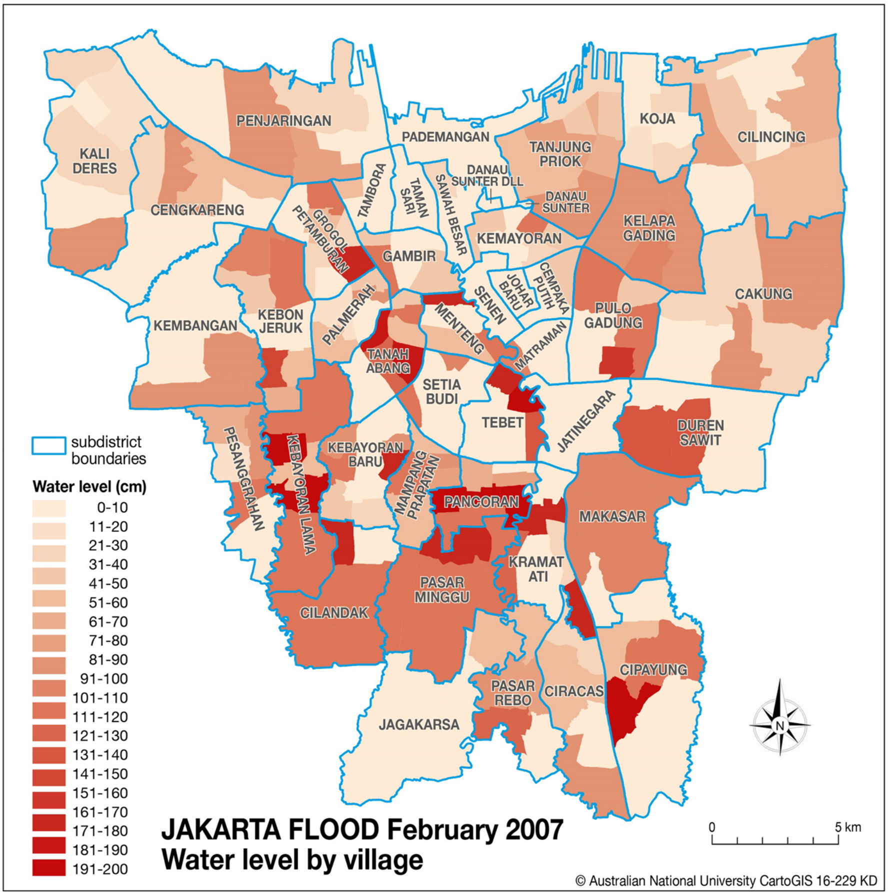

Fig. 1 Map of Jakarta after the flood disaster in 2007. Source: United Nations Department of Safety and Security (UNDSS), 2007

especially during the rainy season (typically from October to April). Those parts of the city further inland are slightly higher but are also at the risk of experiencing flood events (Baker 2011).

Figure 1 shows a map of the study area and the flood water levels during the February 2007 flood event per subdistrict level. As seen, locations with the highest flood level (dark red) are adjacent to the Ciliwung, Pesanggrahan and Sunter Rivers, especially in the southern area of Jakarta. However, the area of the city with more water coverage was northeast Jakarta, which includes the subdistricts of Kelapa Ganding, Pulo Gadung, Cakung, Danau Sunter, Kemoyoran, Tanjung Priok and Cilincing.

The map (Fig. 1) and the data for the flood water levels by village or kelurahan in Jakarta were taken from the UNDSS, which surveyed Jakarta in February 2007. The city is divided into five districts (known as kotamadya), which divide into 42 subdistricts (known as kecamatan). Each subdistrict is comprised of approximately 2–5 kelurahan. The UNDSS collected and reported the water levels of the 2007 Jakarta flood from news sources (radio and television), and United Nations staff reports to UNDSS office and police stations.[2]

The flood water level to be studied in this paper (which is in Fig. 1) corresponds to the water level (measured in centimetres) registered immediately following the flood event on 6 February 2007. This information was gathered at the village level. For our analysis in this paper, we calculate the weighted average flood water level in each subdistrict (kecamatan). The village area (measured in square metres) within each subdistrict is used as a weight to estimate the average water level for each subdistrict. The reasons for aggregating the flood information at subdistrict level are as follows. First, floods in one village (kelurahan) will certainly affect their neighbouring village; second, floods are typically managed at the subdistrict level; and third, for security reasons, household information only contains coded locations at the subdistrict level.

The other data used for this paper are cross-sectional, extracted from the IFLS 2007 dataset. The dataset contains information on monthly house rent, housing characteristics and neighbourhood characteristics.[3] The information extracted is at the subdistrict (kecamatan) level. There are as many as 1539 observations for the city of Jakarta. This sample arguably represents the population of Jakarta (see "Appendix B").

The variables selected for the hedonic price analysis are those commonly used in hedonic property value studies (Yusuf and Koundouri 2005; Yusuf et al. 2009) and are available in the IFLS dataset. Monthly house rental price expressed in million rupiahs (Indonesian currency) is used as a proxy of housing value. Meanwhile, housing characteristic variables are homeowner; house size (expressed in square metres); number of rooms; wall, roof and floor materials; water source and owned toilet availability; and moderately sized yard in the house. Homeowner is depicted as a dummy variable. If a house is occupied by its owner, the homeowner variable is valued as 1, otherwise, zero. The wall, roof and floor materials are dummy variables which have been assigned a value of one if they are constructed from a reasonably durable material, i.e., cement/brick for walls, concrete/roof tiles for roof and cement/stone for floor, or otherwise they are given a value of zero. Water source is also a dummy variable of 1 if there is a water source inside the house, or otherwise zero. Likewise, if a household owns a toilet with septic tank it is 1, otherwise zero. The existence of a moderately sized yard is valued as 1, otherwise as zero. These variables are expected to have a positive relationship to the monthly house rent.

We also include neighbourhood characteristics at the subdistrict (kecamatan) level in Jakarta, namely public transport access, percentage of people with a university education, unemployment rate, distance from the district centre, traffic congestion level and whether or not a house is located close to a river.

The variables for the unemployment rate, the distance to the centre of Jakarta, and the settlements along riverbanks are expected to be negatively associated

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[2] https://trip.dss.un.org/dssweb/WelcometoUNDSS/tabid/105/.

[3] https://www.rand.org/labor/FLS/IFLS.html.

Table 2 Summary statistics of variables in the hedonic equation. Source: 2007 Indonesian Family Life Survey (IFLS) and United Nations Department of Safety and Security (UNDSS)

	Mean	Std. deviation	Max.	Min.
Dependent variable				
Monthly rent (million rupiahs)	5.679	21.253	350	0
Housing characteristics				
Homeowner (1,0)	0.725	0.447	0	1
House size (m^2)	72.849	190.034	3584	4
Number of rooms	5.034	3.112	25	1
Wall material is cement/brick (1,0)	0.878	0.328	1	0
Roof material is concrete/roof tiles (1,0)	0.476	0.500	1	0
Floor material is cement/stone (1,0)	0.843	0.364	1	0
Water source inside (1,0)	0.554	0.497	1	0
Owned toilet with septic tank (1,0)	0.705	0.456	1	0
Moderately sized yard (1,0)	0.277	0.448	1	0
Neighbourhood characteristics				
Accessible by public transport (1,0)	0.757	0.429	1	0
People w. univ. educ. in the neighb. (pct)	9.786	8.259	28.244	0
Unemployment rate in the neighb. (pct)	5.521	3.349	13.043	0
Distance from district centre (km)	0.326	0.469	32	1
Traffic (hourly number of vehicles passing by)	5.596	3.219	11.969	3.151
House located close to a river (1,0)	7.683	6.344	1	0
Environmental variable				
Flood in water level (cm)	42.297	23.109	116.632	0

Number of observations is 1539

with the dependent variable, whereas, the variable for the percentage of people with a university education is estimated to be positively related to monthly housing rent.

On a side note, the variables for accessibility of public transport and traffic need to be carefully interpreted. Access to public transportation is understood to increase the property value as it allows for shorter and more convenient commutes into or within cities (Perticone and Coveney 2017); however, it can also produce negative externalities that lead to adverse effects on housing price such as noise pollution, congestion, and increased construction. On the other hand, traffic can represent the congestion level but also proximity to city attractions and activities.

The environmental variable includes the 2007 flood experience in Jakarta, recorded as the water level measured in centimetres, and it is expected to be negatively associated with house rent.

Table 2 provides a detailed description and summary of the variables that are utilised in the hedonic price model.

4 Empirical modelling

According to Halvorsen and Pollakowski (1981) and Rosen (1974), 'there is no strong theoretical basis for choosing any specific functional form for a hedonic regression' (cited in Malpezzi 2002). Therefore, to determine the model specification to study the effects of a particular property attribute on the housing value, Follain and Malpezzi (1980) tested a linear functional form as well as a log-linear specification, finding that the latter has a number of advantages over the former.

Previous studies show the dependent variable log transformed due to the significant variation in the housing price variable (Skantz and Strickland 1987; Bin and Polasky 2004; Daniel et al. 2007; Bin et al. 2008b; Samarasinghe and Sharp 2010; Pope 2008; Kousky 2010; Bin and Landry 2013). Taking the logarithm of the explained variable minimises the possibility of heteroscedasticity (Gujarati 1995; Wooldridge 2003) or corrects for it between house price (or the house rent) and the residuals (Basu and Thibodeau 1998).

Given the above considerations, the model specification to estimate the coefficients of the housing rental price is as follows[4]:

$$y = \beta_0 + \boldsymbol{\beta}_1 \boldsymbol{x}_1 + \boldsymbol{\beta}_2 \boldsymbol{x}_2 + \boldsymbol{\beta}_3 D_f + \boldsymbol{\beta}_4 \left[D_{\mathrm{f}} f \right] + \varepsilon, \tag{1}$$

where y is the logarithmic form of the monthly rent of the house which is the proxy for housing value, $\boldsymbol{x}_1$ is a vector of housing attribute variables and $\boldsymbol{x}_2$ is a vector of neighbourhood characteristics (see Table 2). The dummy variable D_f assigns a value of one if houses are located in a flood area or otherwise they are given a value of zero. This dummy variable is used to examine whether or not there is a "premium" for houses in the unflooded areas. The variable f is the logarithm form of the flood water and $D_{\mathrm{f}}f$ is an interaction term between the flood zone variable and the logarithm of flood water. This interaction term is to measure the effects of flood on property values within flood zones.[5]

We also observe that other potential source of heteroscedasticity is skewness in the distribution of the regressors included in the empirical model. In this regard, we find that the distribution of the independent variables for house size, number of rooms, and flood has a skewed distribution to the left, while the variable traffic has binomial distribution. By applying a log transformation, a certain level of homoscedasticity is reached (see "Appendix C").

[4] Another option is to use the average treatment effect using the spatial lag model. Assuming a dummy variable of flooding, the house equals one whether it was flooded in 2007 at certain water level (e.g., 30 cm, 50 cm or 60 cm) and above, and zero otherwise. The findings are presented in "Appendix D". Since they are sensitive towards the definition of flooded house or not, this paper prefers to utilise a continuous variable of flood level.

[5] Following Follain and Malpezzi, we test the functional form chosen to determine whether it suits our data set better than that of using a linear model. In this regard, the Box-Cox test was utilised to compare the goodness-of-fit of the two functional forms. Given the results, in our case, they are significantly different in terms of goodness-of-fit; the log-linear function has a lower residual sum of squares compared to that of the linear functional form. Therefore, we use the log-transformed model to look at the coefficients of the empirical model.

Implicit to this model is the assumption that the differential effect of the housing characteristics (homeowner, house size, number of rooms, wall, roof and floor materials, water access, owned toilet and moderately sized yard) is constant across the flood water level, and the differential effect of the flood event is also constant across the property's attributes. That is to say, if the mean housing rental price is higher for a large than for a small house, this is so whether the house is located in a floodplain area or not. Likewise, a house in a floodplain area has a lower mean rental price, this is so whether it is an apartment or a condominium.

As mentioned previously, in this paper, an average flood water level is used for subdistrict (kecamatan) areas. One reason for analysing subdistrict areas is to take into account the impact of nearby flooding on the value of property in a certain area. A subdistrict in the Jakarta context is relatively large enough; however, there is still a possibility that average flood water levels in neighbouring subdistricts affect the property value in a subdistrict (Yusuf et al. 2009).

Anselin (1988) introduced the concept of spatial dependence to determine the relationship among the property values in neighbouring locations. Several studies have incorporated this analysis to estimate the real impact of all the housing attributes—such as Daniel et al. (2007), Bin et al. (2008a), Cho et al. (2009), Samarasinghe and Sharp (2010), Bin and Landry (2013) and Rabassa and Zoloa (2016)—which suggests the presence of this spatial effect in a cross-sectional hedonic price analysis. Ignoring this estimation, the resulting coefficients from the OLS model could be inefficient or inconsistent (Anselin 1988).

To capture the neighbouring spillover effect, this research paper uses the spatial lag model[6] proposed by Anselin (1988) and adopted by various studies (Leggett and Bockstael 2000; Brasington and Hite 2005; Daniel et al. 2007; Bin et al. 2008b; Cho et al. 2009; Yusuf et al. 2009; Samarasinghe and Sharp 2010; Bin and Landry 2013; Rabassa and Zoloa 2016).

This assumes that the housing rental price depends both on its characteristics (structural and neighbourhood) and on neighbouring house rental prices, i.e., the spatial lag model includes the spatially weighted sum of neighbouring house rental prices as the independent variable in the functional form of the housing price formation:

$$y = \beta_0 + \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{\beta}_1 \boldsymbol{x}_1 + \boldsymbol{\beta}_2 \boldsymbol{x}_2 + \boldsymbol{\beta}_3 D_f + \boldsymbol{\beta}_4 \left[D_{\mathrm{f}} f \right] + \varepsilon, \tag{2}$$

where ρ is the spatial dependence parameter and $\boldsymbol{W}$ is an $n \times n$ standardised spatial weight matrix (where n is the number of observations). The spatial matrix, $\boldsymbol{W}$, tells us whether any pair of observations are neighbours. If, for example, house i and j are

[6] Similarly, a spatial error model can be considered, which supposes that spatial dependence arises due to measurement errors or some omitted variables that are correlated and vary spatially. The Lagrange multiplier (statistic = 23.710; p value = 0.000) and the robust Lagrange multiplier (statistic = 12.039; p value = 0.001) tests show spatial error dependence. The spatial error model findings are discussed in more detail in "Appendix E" where it can be seen that the flood coefficient is relatively similar to that of the spatial lag model. This paper prefers to utilise the results for the spatial lag model for its analysis and conclusion, since the spatial lag model is simpler and the spatial correlation can be explicitly seen.

Table 3 Results of basic and spatial lag models

LOG (monthly rent)	Basic OLS	Spatial lag model
Housing characteristics		
Homeowner (1,0)	0.0921 (0.0811)	0.1117 (0.0805)
LOG (size)	0.5479*** (0.0565)	0.5634*** (0.0561)
LOG (rooms)	0.5244*** (0.0799)	0.4859*** (0.0800)
Wall is cement/brick (1,0)	0.2096 (0.1094)	0.2116** (0.1084)
Floor is ceramics/stone (1,0)	0.4152*** (0.1000)	0.4032*** (0.0991)
Roof is concrete/roof tiles (1,0)	−0.0939 (0.0655)	−0.0636 (0.0656)
Water source inside (1,0)	−0.1081 (0.0688)	−0.0697 (0.0691)
Owned toilet with septic tank (1,0)	0.4270*** (0.0840)	0.4439*** (0.0833)
Moderately sized yard (1,0)	0.0319 (0.0758)	0.0312 (0.0751)
Neighbourhood characteristics		
Public transport access (1,0)	−0.0930 (0.0770)	−0.0754 (0.0764)
People w. univ. educ. in the neighb. (pct)	0.0372 (0.0049)	0.0354*** (0.0049)
Unemployment rate in the neighb. (pct)	−0.0271**(0.0109)	−0.0234** (0.0109)
LOG (distance)	−0.1804*** (0.0552)	−0.1755*** (0.0547)
LOG (traffic)	−0.1361 (0.0987)	−0.0922 (0.0987)
House located close to a river (1,0)	−0.2134*** (0.0688)	−0.2416*** (0.0687)
Environmental variable		
Flood zone (1,0)	0.3427 (0.2159)	0.2897 (0.2145)
Flood zone (1,0) × LOG (flood)	−0.1002** (0.0508)	−0.0952* (0.0503)
Constant	10.9749	13.8331
Rho	n/a	−0.2133***
Number of observations	1539	1539
R-squared	0.478	n/a
Variance ratio	n/a	0.482
Squared corr.	n/a	0.482
Moran's *I* statistic	−7.714***	n/a
LM lag	n/a	18.319***
RLM lag	n/a	6.648***

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level. Numbers in brackets are standard deviations

neighbours, then $w_{i,j} = 1$ and zero otherwise, for all $i \neq j$. Please note that $w_{i,i} = 0$ for all i.

Whether any pair of houses is neighbouring in this paper is determined by them sharing some common borders (contiguity). The spatial weight matrix is usually standardised, such that every row of the matrix is summed to 1. This enables us to interpret the spatial lag term in a spatial model as a simply spatially weighted average of neighbouring house prices.

The spatial lag model will be estimated using a maximum likelihood (ML) regression technique (Anselin 1988).

5 Results and discussion

Table 3 shows the results of estimating the basic and spatial lag models, i.e., Equations (1) and (2), respectively. From the results for the spatial lag model, it can be seen that the ρ estimate is significant at 1%. The Moran's I statistic shows a negative spatial autocorrelation in house rental prices in 2007, denoting that observations with similar rental prices are dissimilar when compared.

By comparing results for the basic and spatial lag models, it can also be seen that while most coefficients are almost similar, the coefficients for homeowner,[7] house size, number of rooms, floor and roof materials, water source and owned toilet, public transport access, traffic flow, house located close to a river and flood water level are relatively different. These results indicate that spatial dependence plays an important role in the process of formulating housing rental prices in the Jakarta housing market, i.e., estimated coefficients of the basic model are likely to be inefficient or inconsistent. The results from the spatial lag model are argued to be superior to those of the basic model.[8]

When observing the results for the spatial lag model, seven out of nine house structural characteristics, i.e., homeowner, house size, number of rooms, wall and floor materials, owned toilet and moderately sized yard, are positively associated with the house rental price. This is as expected. Estimated coefficients for these variables are strongly significant at the 1% and 5% level, except for the homeowner and moderately sized yard, which are not significant at a conventional level. The other two estimated coefficients, i.e., roof material and water source, are negatively related to the dependent variable but not statistically significant; however, the negative signs are unexpected.

The estimated coefficients for neighbourhood qualities have the expected sign. Four out of six comply with expectations and are statistically significant correlated with housing rent price, i.e., with the coefficient for the percentage of people with a university degree, the distance to the centre and the house located close to a river, all significant at the 1% level. The coefficient for the percentage of people with a university degree is positively related to housing rental price. The distance to the centre of Jakarta is negatively associated with housing rental price, meaning the closer the house is to the business centre, the higher the rental price charged to the tenant. Finally, the closer the house located close to a river, the lower the housing rental price.

[7] Additionally, an OLS regression is applied to analyse whether or not the effects of flooding on rental prices for Jakarta residents are similar for both owner occupied and rentals. The results of this analysis are shown in "Appendix F" and indicate that rentals are more likely to be vulnerable to impacts of flooding.

[8] Housing attributes are mainly represented by dummies, so it is possible the OLS model has a certain degree of multicollinearity. This could explain the low significance levels and opposite signs obtained from a linear regression. Variance inflation factors (VIFs) are used to test for multicollinearity among the independent variables. According to Gujarati (1995), multicollinearity may be a problem if the VIF is greater than 10. In this study, the mean of the VIF values for all of the variables was 1.90 for the OLS regression. This means there is no multicollinearity or no correlation between the independent variables.

Regarding the main variable of analysis in this paper, namely flooding, it can be seen from the spatial lag model in Table 3 that there is no premium monthly rental price to live in an unflooded area—that is, people do not have a willingness to pay more to live outside the flooded areas, as the dummy variable of flood shows a positive sign and is not statistically significant. One plausible explanation for this is the fact that 40% of Jakarta lies below sea level and is continuously under severe threat of flooding every year; with this flood hazard expected to intensify in the future (Garschagen et al. 2018).

Further to this, the coefficient of the flood water level has a negative sign as expected, and statistically significant at 10%. It can be said that a 1% increase in flood water will lower the housing rent by 0.0952%. This is the implicit price obtained from the derivative of the monthly rent with respect to the environmental attribute, in the hedonic model. In a spatial log-linear model, the willingness to pay (WTP) to avoid negative impacts of floods equals the estimated coefficient for that characteristic multiplied by the dummy variable (D_{f}), or

$$\frac{\partial y}{\partial f} = \boldsymbol{\beta}_4 D_{\mathrm{f}}. \tag{3}$$

However, Eq. (3) can be reformulated by applying log-transformation rules on both sides to obtain the new equation as follows:

$$\mathrm{WTP} = D_{\mathrm{f}}\mathrm{flood}^{\wedge\beta 4}, \text{ when } D_{\mathrm{f}} = 1. \tag{4}$$

Therefore, by inserting the average flood water level in Jakarta in 2007 to Eq. (4), which was approximately 42.30 cm and considering its estimated coefficient (0.0952), it can be roughly concluded that flooding in Jakarta lowers the monthly housing value by Rp. 700 thousand or USD 76.24.

If this Rp. 700 thousand can be interpreted as the average monthly willingness of a household to 'permanently' get rid of the cost of flooding, i.e., the capitalised marginal willingness to pay (MWTP), and assuming that there are approximately 10 million people or 1.82 million households in Jakarta having houses with an average lifetime of 25 years and a discount rate of 5% annually, it can be estimated that the total willingness of all households in Jakarta to permanently get rid of the cost of flooding is approximately Rp. 45.8 trillion or approximately 8.1% of Jakarta's GDP in 2007.

The formula to calculate the capitalised MWTP is as follows:

$$W = \sum_{t=0}^{25} {}^{w}\!/_{(1-r)^t}, \tag{5}$$

where W is the capitalised marginal willingness to pay, i.e., how much a household is willing to pay for a 'permanent' (typically 25 year) elimination of flood, and w is the total marginal willingness to pay of the whole households in Jakarta per year, i.e., marginal effect of hedonic equation multiplied by 12 months and multiplied by 1.8 million households (or approximately Rp. 15 trillion), while r is a discount rate of 5% and t is year.

6 Conclusion

This study is an attempt to estimate the cost of flooding in developing countries' megacities by conducting a hedonic price analysis of the Jakarta housing market, which estimates the correlation between levels of flooding and monthly housing rental prices in Jakarta in 2007. Data on the flood water levels by subdistrict or kecamatan in Jakarta were obtained from the United Nations Department of Safety and Security (UNDSS), which collected and reported the water levels of the 2007 Jakarta flood from news sources (radio and television), and United Nations staff reports to the UNDSS office and police stations. Data on monthly housing rental prices and other information related to house and neighbourhood characteristics are taken from the IFLS for 2007.

The empirical results in this paper indicate that floods have a negative association with housing rental prices. It is estimated that a 1% high flood water level is associated with a 0.124% lower monthly housing rental price; or, on average, flooding in Jakarta is associated with lowering monthly housing values by approximately Rp. 700 thousand. Furthermore, if this number can be interpreted as an average monthly willingness of a household to 'permanently' get rid of the cost of flooding, this paper estimates that the total willingness of all households in Jakarta to get rid of the cost of flooding annually is approximately Rp. 15 trillion, and to permanently get rid of flooding is approximately Rp. 45.8 trillion or approximately 8.1% of Jakarta's GDP in 2007.

When put in the context of the potential cost to comprehensively mitigate flooding in Jakarta, which the Jakarta Water Management Agency estimates as being Rp 118 trillion (Tambun et al. 2015), this is considerably lower (by approximately Rp 72.2 trillion) but has the potential to increase due to insufficient resources to offset the annual cost of floods.

An ongoing management plan with a budget of Rp 2.5 trillion annually is being developed and implemented (World Bank 2016), whereas the real flood cost will continue to occur, so it is likely to result in higher expenditure as they "keep up" with rehabilitation and maintenance over time.

It is therefore clear that it will be challenging for the Jakarta government to extract sufficient resources from its society to fund projects to eliminate flooding in the city indefinitely. External resources from the central government are most likely needed to resolve the problem of flooding in Jakarta. Until then, a constant exposure of the urban areas in developing countries to flood damage will most likely keep happening.

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Appendix A: Hedonic property value method

The hedonic price method provides an intuitive analytical tool for studying the effects of property attributes and spatially integrated amenities on housing prices. Lancaster (1966) pioneered the development of its theoretical foundations, derived from the theory of consumer demand. The central assumption is that consumer utilities are not based on the goods per se, but instead on the individual "characteristics" of goods—their composite attributes. Although Lancaster (1966) was the first to discuss hedonic utility, there was nothing about pricing models and the properties of market equilibrium. To fill this gap, Rosen (1974) studied the demand–supply interaction in which they bid (consumers) and offer (suppliers) the combination of attributes and prices of the goods that keep the market in equilibrium.

Additionally, Rosen's (1974) studies form the basis for using the hedonic property price model to estimate the value of environmental amenities. The argument is that the attributes of residential properties—recognised as heterogeneous goods, such as structural, neighbourhood and environmental characteristics—are reflected in the price differentials that affect lessee preferences in a market clearing equilibrium condition (Rosen 1974). The advantage of using this method over other preference estimation techniques is that it makes use of actual market transactions to recover value estimates for non-market attributes (Bin et al. 2008a). These related to aesthetic sights and their closeness to recreational sites such as parks, and beaches, as well as the quality of the environment in terms of air, water and noise pollution.

According to this method, the hedonic price function is typically represented as:

$$P_i = f(s, n, l, e), \tag{6}$$

where P_i is the price of property i which is a function of structural characteristics (e.g., house size, number of rooms, quality of walls), s; neighbourhood characteristics (for example, ethnic composition, crime rate, flow of traffic), n; location characteristics (e.g., proximity to economic centres, distance to highways, accessibility to public transport), l; and environmental characteristics (such as air pollution and flooding), e. Therefore, characteristics that generate benefits for households, such as a larger number of rooms or home size, increase the property's price, while characteristics that imply costs for households, such as a neighbourhood with a high crime rate, reduce the property's price.

Given that the basis of the method is to find what portion of the price is determined by the hedonic variable, we obtain the environmental attribute (which is flooding) by calculating the partial derivative of the price with respect to the variable e, $\partial P_i / \partial e$. It gives us the marginal implicit value for an additional unit of the environmental asset, and thus enables an estimate of its monetary value.

Appendix B: Mean comparison between IFLS and SUSENAS datasets

To support the representation of Jakarta's population, we provide the means of certain variables from Indonesia–National Socio-Economic Survey (SUSENAS) 2007 that was accessed for this paper. The following table shows the means compared with those of IFLS 2007 (Table 4).

Table 4 Mean comparison between IFLS and SUSENAS datasets. Source: IFLS and SUSENAS, for year 2007

	IFLS	SUSENAS
Housing characteristics		
Homeowner (1,0)	0.725	0.625
Wall material is cement/brick (1,0)	0.878	0.889
Roof material is concrete/roof tiles (1,0)	0.476	0.618
Floor material is cement/stone (1,0)	0.843	0.976
Water source inside (1,0)	0.554	0.566
Neighbourhood characteristic		
People w. univ. educ. in the neighb. (pct)	9.786	10.973

For the IFLS variables, the number of observations is 1539; for the SUSENAS housing characteristics variables, the number of observations is 6832; and for the SUSENAS neighbourhood characteristic variable is 14,408

Appendix C: Distribution of independent variables

The below table represents the distribution of continuous variables when they are in levels. Those on the left, demonstrate the skewed towards zero on the axis, while those on the right demonstrate a spread across the axis (i.e., closer to normal distribution) (Fig. 2).

Appendix D: Spatial average treatment effect model

Unlike previous studies, this study uses a continuous measure of flood water (in centimetres) in the empirical analysis. To find whether or not a house within the flooded area lowers the rental price at any certain water level, we construct a conventional binary measure of flooding at the neighbourhood level based on three different threshold water levels, e.g., 30, 50 and 60. A house is considered flooded when the water level in the area during the flood event in 2007 was 30 cm (or 50 cm or 60 cm) and above; otherwise, the house is considered not flooded. We then estimate the impact of flooding on location rental prices using the spatial lag model:

$$y = \beta_0 + \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{\beta}_1 \boldsymbol{x}_1 + \boldsymbol{\beta}_2 \boldsymbol{x}_2 + \boldsymbol{\beta}_3 D_{\mathrm{f}} + \varepsilon. \tag{7}$$

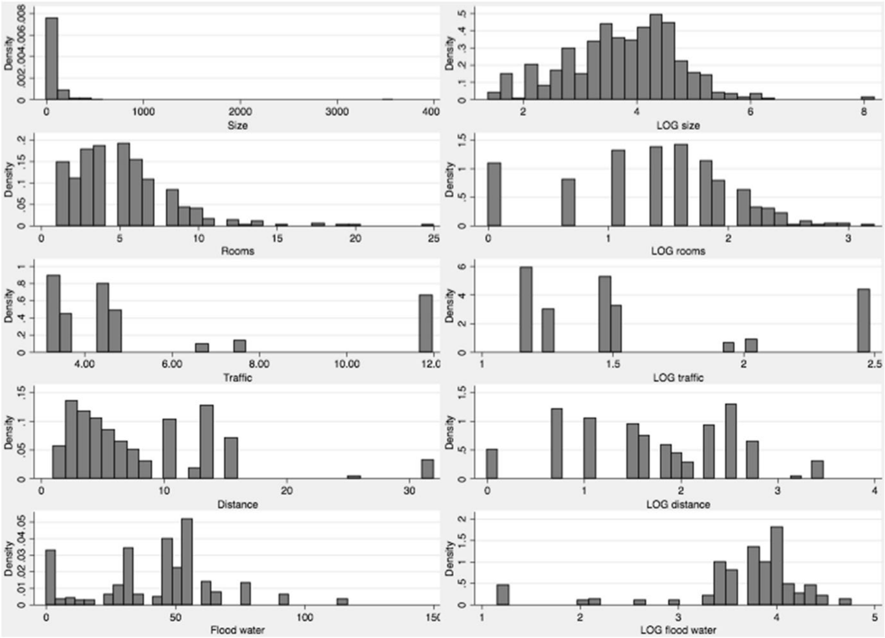

Fig. 2 Distribution of independent variables in levels and log transformed

From Table 5, it can be seen that results are sensitive towards the definition of being flooded or not, i.e., flood water thresholds define whether the house is flooded or not. However, it should be considered that any marginal difference between the chosen flood levels (e.g., from 30 to 50 cm and 50 to 60 cm) could be irrelevant and trivial for a household, as they are still experiencing flooding with its associated damage to the home. Therefore, we prefer to use a continuous flood-level variable as our main variable of interest.

Table 5 Results of spatial average treatment effect. Source: Indonesian Family Life Survey (IFLS) and United Nations Department of Safety and Security (UNDSS)

LOG (monthly rent)	Spatial lag model		
	(> 30 cm)	(> 50 cm)	(> 60 cm)
Housing characteristics			
Homeowner (1,0)	0.1109 (0.0804)	0.1228 (0.0804)	0.1256 (0.0806)
LOG (size)	0.5655*** (0.0560)	0.5635*** (0.0561)	0.5621*** (0.0561)
LOG (rooms)	0.4797*** (0.0800)	0.4997*** (0.0801)	0.4853*** (0.0800)
Wall is cement/brick (1,0)	0.2079* (0.1083)	0.2038* (0.1084)	0.2003* (0.1085)
Floor is ceramics/stone (1,0)	0.4048*** (0.0990)	0.3924*** (0.0989)	0.3915*** (0.0990)
Roof is concrete/roof tiles (1,0)	−0.0604 (0.0654)	−0.0957 (0.0659)	−0.0676 (0.0655)
Water source inside (1,0)	−0.0731 (0.0691)	−0.0535 (0.0693)	−0.0645 (0.0691)
Own toilet with septic tank (1,0)	0.4385*** (0.0834)	0.4469*** (0.0833)	0.4546*** (0.0836)
Moderately sized yard (1,0)	0.0318 (0.0748)	−0.0003 (0.0747)	0.0210 (0.0747)
Neighbourhood characteristics			
Public transport access (1,0)	−0.0856 (0.0765)	−0.0520 (0.0764)	−0.0524 (0.0766)
People w. univ. educ. in the neighb. (pct)	0.0337*** (0.0047)	0.0336*** (0.0047)	0.0341*** (0.0048)
Unemployment rate in the neighb. (pct)	−0.0201* (0.0109)	−0.0217** (0.0109)	−0.0285*** (0.0107)
LOG (distance)	−0.1556*** (0.0547)	−0.1530*** (0.0552)	−0.1784*** (0.0549)
LOG (traffic)	−0.0979 (0.0966)	−0.1945* (0.1008)	−0.1206 (0.0960)
House located close to a river (1,0)	−0.2564*** (0.0686)	−0.2130*** (0.0703)	−0.2178*** (0.0705)
Environmental variable			
Flood zone (1,0)	−0.1811** (0.0825)	0.1308 (0.0814)	−0.1182 (0.0938)
Constant	14.1840	13.9628	13.7956
Rho	−0.2329***	−0.2230***	−0.2076***
Number of observations	1539	1539	1539

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level

Appendix E: Estimation results using spatial error model

The spatial error model takes the following form:

$$y = \beta_0 + \boldsymbol{\beta}_1\boldsymbol{x}_1 + \boldsymbol{\beta}_2\boldsymbol{x}_2 + \boldsymbol{\beta}_3 D_f + \boldsymbol{\beta}_4\left[D_f f\right] + \varepsilon; \quad \varepsilon = \lambda \boldsymbol{W}\varepsilon + \mu, \tag{8}$$

where μ is the independent and identically distributed (i.i.d.) error term and λ is the spatial error parameter. The understanding of the spatial error model is close to the moving average model, whereby each observation error in the time series can also be affected by other observation errors. Ignoring the spatial error term, the OLS coefficients will be inefficient as it violates the assumption of independence among disturbance terms (Anselin 1988) (Table 6).

Table 6 Results of spatial error model

LOG (monthly rent)	Spatial error model
Housing characteristics	
Homeowner (1,0)	0.1403*** (0.0809)
LOG (size)	0.5675*** (0.0558)
LOG (rooms)	0.4751*** (0.0797)
Wall is cement/brick (1,0)	0.2005*** (0.1089)
Floor is ceramics/stone (1,0)	0.3926*** (0.0992)
Roof is concrete/roof tiles (1,0)	−0.0549 (0.0647)
Water source inside (1,0)	−0.0627 (0.0686)
Own toilet with septic tank (1,0)	0.4432 (0.0836)
Moderately sized yard (1,0)	0.0291* (0.0750)
Neighbourhood characteristics	
Public transport access (1,0)	−0.1170 (0.0786)
People w. univ. educ. in the neighb. (pct)	0.0352*** (0.0055)
Unemployment rate in the neighb. (pct)	−0.0326*** (0.0104)
LOG (distance)	−0.2222*** (0.0505)
LOG (traffic)	−0.1465 (0.0913)
House located close to a river (1,0)	−0.2640*** (0.0735)
Environmental variable	
Flood zone (1,0)	0.5535** (0.2911)
Flood zone (1,0) × LOG (flood)	−0.1476*** (0.0552)
Constant	11.7029
Lambda	−0.6505***
Number of observations	1539
R-squared	n/a
Variance ratio	0.417
Squared corr.	0.417

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level. Numbers in brackets are standard deviations

Appendix F: Owner-occupied and rental property comparison

When running separate regression for the dummy variable homeowner (1,0), we find that the study variable (*LOGflood*) is statistically significant at 5% for rental properties. This means that those renting are likely to be more vulnerable to flood impacts than those owning or buying. Owning a home can be considered as an indicator of income and economic resources that may support flood victims to cope with the effects of flooding (Table 7).

Table 7 Results of OLS for both owner-occupied and rental properties

LOG (monthly rent)	OLS model	
	Homeowner	Rental
Housing characteristics		
LOG (size)	0.5961*** (0.0666)	0.2421** (0.1007)
LOG (room)	0.5597*** (0.0977)	0.6332*** (0.1311)
Wall is cement/brick (1,0)	0.2217 (0.1510)	0.1199 (0.1531)
Floor is ceramics/stone (1,0)	0.5100*** (0.1299)	0.3484** (0.1441)
Roof is concrete/roof tiles (1,0)	−0.0364 (0.0779)	−0.2151** (0.1152)
Water source inside (1,0)	−0.1786** (0.0826)	0.0700 (0.1213)
Toilet with septic tank (1,0)	0.5331*** (0.1075)	0.1271 (0.1295)
Yard is moderately sized (1,0)	0.0154 (0.0891)	−0.0183 (0.1382)
Neighbourhood characteristics		
Accessible by public transport (1,0)	−0.0434 (0.0908)	−0.2241 (0.1370)
People w. univ. educ. in the neighb. (pct)	0.0451*** (0.0057)	0.0107 (0.0091)
Unemployment rate in the neighb. (pct)	−0.0265** (0.0129)	−0.0207 (0.0195)
LOG (distance)	−0.2203*** (0.0653)	−0.0152 (0.0968)
LOG (traffic)	−0.2403** (0.1204)	0.3800** (0.1648)
House located close to a river (1,0)	−0.1916** (0.0820)	−0.1772 (0.1182)
Environmental variable		
Flood zone (1,0)	0.2667 (0.2520)	0.7049* (0.3976)
Flood zone (1,0) × LOG (flood)	−0.0816 (0.0611)	−0.2170** (0.0867)
Constant	10.7725	11.3239
Number of observations	1116	423
R-squared	0.468	0.333

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level. Numbers in brackets are standard deviations

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