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Demand for index-based flood insurance in Jakarta, Indonesia

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Abstract
Most megacities in developing countries are constantly exposed to flood risk, with a clear lack of understanding of insurance leading to poor risk management by urban populations. This paper analyses the demand for a hypothetical index-based flood insurance product among households in Jakarta, Indonesia. An expected utility framework is used to test whether this demand is significantly determined by the basis risk component of the insurance. The paper investigates the effects on insurance uptake of premium discounts, and risk aversion. Using distance of a house to the reference floodgate station (a proxy for basis risk), we find demand falls as basis risk increases. Additionally, the uptake decreases with price and risk aversion. We recommend further investment in floodgate stations to reduce basis risk, complemented with subsidies to encourage demand for this product. However, the level of discount offered to urban households is inconclusive and constitutes an important topic for future research.

Key words: index insurance, basis risk, disasters, floods, Indonesia.

JEL Code: D81; G22; Q54

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1. Introduction

Changes in extreme weather and climate events can have large impacts on human health and cause losses to wealth. There has been growing evidence showing that the ongoing trend of climate change contributes to higher temperatures that will exacerbate weather-related events in the coming decades, such as flooding and drought (IPCC, 2012; IPCC et al., 2018; UNDRR, 2019). In turn, this increases the vulnerability of communities to natural hazards, especially those in developing countries characterised by poverty and limited coping capacity. To improve developing countries' capacity, mechanisms such as weather-related insurance are considered to reduce or compensate for economic and financial losses. This risk transfer instrument can speed-up rebuilding and recovery processes by providing post-disaster funding and liquidity soon after the natural event (Kousky, 2019).

Index-based insurance[1] has emerged as a new type of financial risk transfer product helping to overcome issues commonly identified under traditional insurance policies (Barnett and Mahul, 2007; IFAD, 2010). More specifically, it removes the problems of moral hazard (hidden action) and adverse selection (hidden information) – considered advantageous to the insurer – compared to traditional insurance (Barnett et al., 2008; Cole et al., 2013). This type of insurance has become prominent as a solution for poor management of land and water resources, and instances of people being exposed to flooding. In particular, index-based flood insurance protects against damage resulting from flood incidences due to heavy rainfall. Unlike indemnity-based insurance, where the policyholder receives compensation for verifiable losses, this product pays out claims based on observable and measured flood indices that are correlated with losses suffered by policyholders.

[1] This product is classified as a derivative which differs from traditional insurance (known as indemnity-based contracts).

In that context, this study proposes a hypothetical product based insurance on flood-related indices for households located in the megacity of Jakarta, Indonesia, which suffers from annual flooding. This product would compensate urban households against actual losses such as housing maintenance repairs, clean-up costs, income loss, and costs related to evacuation[2]. However, this beneficial aspect of the insurance product also presents a problem: basis risk, the situation whereby the insured faces uncertainty that its actual losses are not fully covered.

Some experimental studies explore these same factors to assess their collective impact on the demand of smallholder farmers in developing countries purchasing index-based insurance. Their findings show that insurance adoption is negative (and highly sensitive) to prices and distance to the station (basis risk); and demand increases at low levels of risk aversion, then decreases at higher levels (Mobarak and Rosenzweig, 2013; Hill et al., 2013; Cole et al., 2013; Hill et al., 2016).

The purpose of this paper is to test how demand for this insurance product behaves under basis risk, and the response to premium and risk aversion using a hypothetical index-based flood insurance for the urban context of Jakarta, Indonesia. This megacity was selected for our study due to a number of reasons. First, it is one of the biggest and most populated in the world, and vulnerable from flooding due to the occurrence of annual flood-related disasters (Firman et al., 2011; Cobian and Resosudarmo, 2019). This condition comes as a result of: i) high rainfall intensity; ii) subsidence soil; and iii) inadequate hydraulic infrastructure in the city (Sedlar, 2016). In addition, parts of north Jakarta are sinking at an average rate of 15 centimetres (cm) per year, making Jakarta the world's fastest sinking city (Octavianti and Charles, 2018).

[2] These are the most common household expenditures due to flooding in Jakarta, based on the individual's responses from our survey.

Second, the annual cost of these floods has been significant; for example, the 2007 flood, which is considered the worst natural shock, caused a total loss of US$ 565 million in terms of property damage (Wijayanti et al., 2017). Third, to improve the capabilities of Jakarta's residents to cope with this annual flood event, there has been discussion on the possibility of developing an index-based flood insurance product. This product may insulate household income and consumption against flood shocks that are exogenous to the household unit.

We achieve the paper's objective by using data from a double-bounded dichotomous choice experiment conducted in 2018, combined with five-year flood data. We use as a proxy of basis risk the distance of a household to the reference floodgate station in the hypothetical insurance product they were offered. Our identification strategy leverages the exogeneity of the distance to the station after controlling distance of a household to the closest river and household's characteristics, as well as premiums and risk aversion, in order to exploit these exogenous variations to identify the effects on demand. To the best of our knowledge, it is one of the first studies to examine features of demand for index-based flood insurance in the urban context of a developing country.

The results of this study are in line with those of previous study estimates, showing that demand falls with price and distance to the floodgate station, while insurance uptake only decreases at extreme risk averse households. In addition, we find that households located equal to and less than five km away from the reference floodgate station are four times as sensitive to prices (demand is elastic) as those households located equal to or more than 12 km away.

The remainder of the paper is structured as follows. The next section defines index-based insurance, providing the theoretical framework and literature review. It is followed by a section describing the household survey on index-based flood insurance in Jakarta. The next section is on the identification strategy and the econometric framework; then, sections on main results and extended analysis, and lastly the conclusion section.

2. Index-based insurance: Theoretical framework and literature review

Index-based insurance compensates the insured based on pre-agreed weather-related indices – measured with historical information recorded at monitoring stations – that represent actual losses within a geographically defined space (Skees and Barnett, 2006). In agriculture, for example, temperature and precipitation gauge information is used to model drought and rainfall crop yields. If weather-related indices remain below or cross pre-defined thresholds, compensation is released to the insured.

With index-based flood insurance, the index is typically constructed based on data related to the extent and depth of water level, and the amount of time for flooding to subside. Floods occurring generally near a body of water (mostly rivers) are known to be unevenly distributed across space – in the same way that precipitation is identified as an idiosyncratic shock in Dell et al. (2014). Under this approach, every household within a similar spatial area with the same insurance policy and damage experience from flooding receives identical payouts despite actual losses. Hence, indemnity payments are based on objective, observable, and verifiable variables.

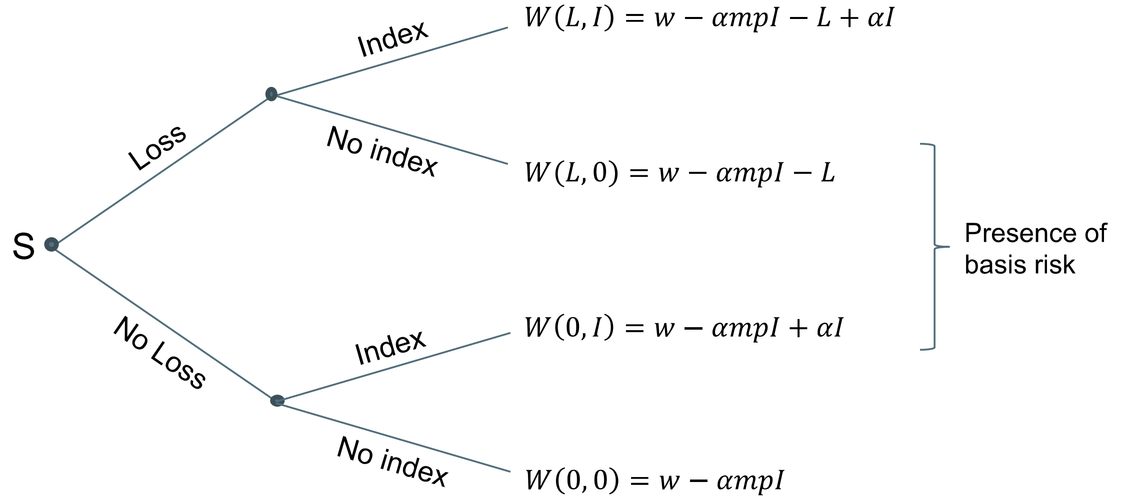
Following the approach of Hill, Robles and Ceballos (2016), complemented with elements of Clarke's (2016) work, a standard expected utility model for index-based insurance is adapted to explore predictions on whether insurance demand behaves as expected in response to basis risk, premium and risk aversion. Consider a representative urban household that is strictly risk-averse[3], with welfare W, and faces two states of the world $S = \{Loss = L,\ Loss = 0\}$; where $Loss = L$ with probability p if the household

[3] A risk-averse household with indirect utility function satisfies Constant Absolute Risk Aversion (CARA). This means as wealth increases a household holds the same amount of dollars in risky assets.

suffered from a disaster, and $Loss = 0$ with probability $1 - p$, if they did not. In the absence of insurance, the expected welfare is $E[W|S] = p(w - L) + (1 - p)(w - 0) = w - p.L$.

In the presence of index-based insurance, the maximum payout claimed by an insured household is I when facing losses after a bad natural event occurs. Hence, the expected amount of claim per household is pI. The premium of the index-based insurance is equal to mpI, where m is known as "price multiple" that places it above or below the expected claim. Therefore, when $m = 1$, it is an actuarially-fair price; $m > 1$ is an actuarially-unfair price; and $m < 1$ is a favourable product priced below the actuarially-fair price.

The urban household can choose an index insurance coverage as high as α, where $0 < \alpha \leq 1$. This urban household would face four possible scenarios when flooding occurs in the neighbourhood area as shown in Figure 1. These are combinations of joint events: i) household experiences or not $Loss$ ($= L$) due to flooding; and ii) whether or not the weather-related index crosses a pre-determined threshold to trigger a payout; i.e. the compensation ($= I$) is released or not.



Notes: Loss = scenario for a household experiencing loss equal to L due to flooding; No Loss = scenario for a household experiencing no loss; Index = scenario for a weather-related index crossing a pre-defined threshold and compensation I released; No Index = scenario for a weather-related index placed below a pre-defined threshold.
Source: Author's illustration.

Fig. 1 Possible scenarios of households' welfare with index-based insurance when flooding occurs

The presence of basis risk is associated with a joint probability distribution (r) of some loss experienced by the household due to flooding and the weather-related index placed below a pre-defined threshold – i.e. household facing the worst scenario $W(L, 0)$, or no loss experienced by the household but the weather-related index crosses a pre-defined threshold – i.e. household facing the best scenario $W(0, I)$. In these two scenarios, basis risk is not zero (or r>0). In contrast, a perfect weather index insurance is one that has no basis risk (r=0).

The household decision problem consists of maximising its expected indirect utility by controlling α:

$$\max E[W|S] = E[w - \alpha mpI - L(S) + \alpha I(S)] \tag{1}$$

The first-order condition is as follows:

$$E\left[W'(S)\frac{\partial W(S)}{\partial \alpha}\right] = 0 \tag{2}$$

Basis risk (r) indirectly impacts the expected welfare through the optimal choice of α. In the absence of basis risk ($r = 0$) and an actuarially-fair price ($m = 1$), the optimal solution is $\alpha^* = 1$.

Given the presence of basis risk with an actuarially-fair price insurance product, we expect to see a downward demand curve with respect to levels of household risk aversion (from least to extreme risk-aversion), however it may not be monotonic. In any case, we predict a least risk averse household willing to purchase insurance ($\alpha = 1$), while an extremely risk-averse household unwilling to purchase insurance ($\alpha = 0$).

The demand for index insurance would be also affected by the magnitude of m (the price factor) when it is different from 1, $m \neq 1$. A household's welfare is negatively impacted by an actuarially-unfair price ($m > 1$) and basis risk ($r > 0$) when the disaster occurs, resulting in a low probability of purchasing the index insurance. Therefore, given possible variations of price and non-price factors – namely the payout relative to the product price, and the degree of basis risk and risk-aversion – in the household's decision problem, the shape of index-based insurance demand becomes an empirical question.

There exists experimental research focusing on the impact that price and non-price factors have on index-based insurance demand, including those in developing countries (Giné et al., 2008). Index-based insurance literature, focusing on analysis of paying a price in return for a future payout using discounts randomly allocated among households to generate exogenous price variation for insurance uptake, shows that, as prices decline via incentives, the probability of purchase increases. This is exacerbated when index-based insurance is below or at an actuarially-fair price, showing that demand is clearly sensitive to these variations for risk-averse households (Cole et al., 2013; McIntosh et al., 2013; Takahashi et al., 2016; Tadesse et al., 2017; Jensen et al., 2017). By contrast, for insurance products with an actuarially-unfair price – with or without discounts, household demand increases with risk-seeking and decreases with risk-averse households (Hill et al., 2016; Clarke, 2016).

Basis risk, however, has been under-researched within index-based insurance literature in the developing country context (Jensen et al., 2016), despite being a major issue substantially reducing demand for insurance. Few studies posit approaches to proxy for basis risk; for example, Giné et al. (2008) use *accumulated rainfall* to consider when a farmer decides to sow seeds[4], and *share of cultivated land used for castor and groundnut crops*[5] to infer if the farmers' planting decision coincides with precipitation measurements collected at the gauge. Another proxy – used in Deng et al. (2007), Gaurav and Chaudhary (2020), and Ceballos and Robles (2020) – is the *degree of correlation* between two sets of weather indices collected at the weather station and the household's plot, finding that basis risk

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4 This proxy is a dummy equal to one if a farmer decides to sow based on accumulated rainfall (due to the approximate 2-month verification delay following rainfall occurring and the government making a payout), and zero if instead the decision is based on other factors such as soil moisture and advice from other farmers (which are non-reliant on government verification).

5 If a household grows castor or groundnut crops, which are related to the presence of low rainfall and associated with the insurance design product, they were more likely to purchase insurance.

decreases when the coefficient is closer to 1. Finally, Mobarak and Rosenzweig (2013), McIntosh et al. (2013), Hill et al. (2016), and Sibiko et al. (2018) use *distance to the weather station* to measure the basis risk degree of index-based insurance, finding that pay-outs for shorter distances are more closely correlated with actual losses of the insured. A similar proxy is used in this study – distance of a house to the reference floodgate station.

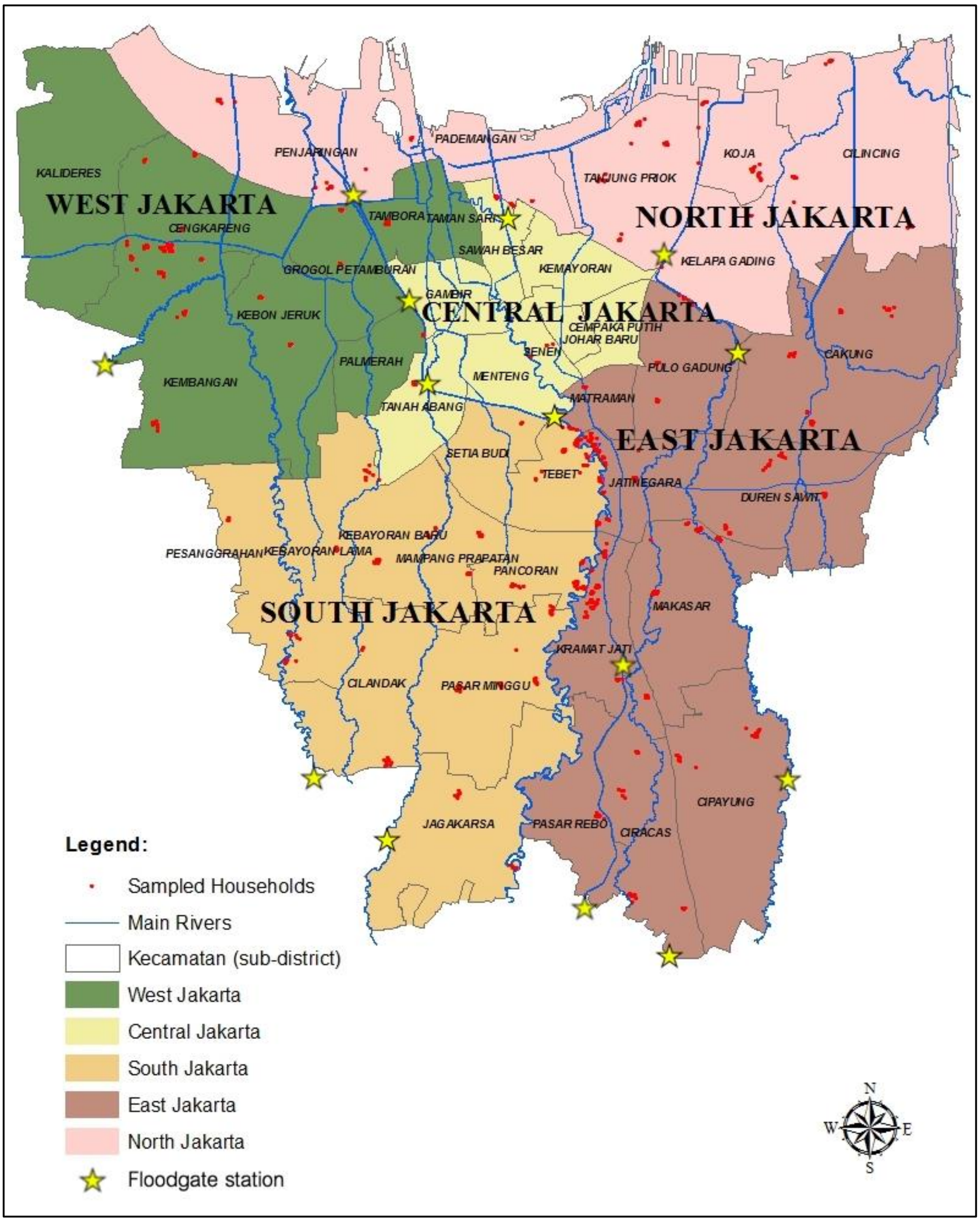
3. Household survey on hypothetical index-based flood insurance in Jakarta

A household survey was conducted for a month between February and March in 2018 to collect basic information on household characteristics, including age, gender, number of members, years of education, income and consumption, and housing ownership; geographic characteristics; and experience with flood shocks. The survey also included a specialised module regarding demand for a hypothetical index-based flood insurance product, premium rates, discounts, and risk attitudes.

Given that areas in Jakarta are exposed to different flood risks, we classified each *Rukun Warga* (RW), or sub-village (*kelurahan*), in Jakarta into three categories: i) almost never experienced flood; ii) occasionally experienced flood; and iii) always experienced flood. This classification used data on flood water level at RW level collected by the *Badan Penanggulangan Bencana Daerah* (BPBD or Jakarta Regional Disaster Management Agency)[6] for the period 2013-2016. In collaboration with the Indonesian statistical agency, the Statistics Indonesia, we then sampled 1,200 households, equally distributed across "almost never flooded", "occasionally flooded" and "always flooded" areas. A total of 836 households completed the survey, which 258 of them are in the "almost never flooded"

6 A flood event is defined as an overflow of river water with a height of 40cm and above. According to Cobian and Resosudarmo (2019), approximately from this flood height, households start experiencing property damage associated with flooding. In addition, we did not use data on elevation with respect to sea level to allocate villages to any category because of the significant variation across locations with houses that have or have not experienced floods in the 2013-2016 period.

category, 289 in the "occasionally flooded" category, and 289 in the "always flooded" category. Figure 2 maps the household locations of survey participants in Jakarta, and the areas covered including within and outside of flood hazard zones, and closer to and far from main rivers.



Notes: This figure shows the regions of our study area, the households who participated in the survey, and the location of the reference floodgate stations used for triggering payouts of the hypothetical index-based flood insurance.
Source: Author's own illustration.

Fig. 2 Location of study area, sampling sites and reference floodgate stations

A unique hypothetical index-based flood insurance product was offered in each surveyed household. The product would pay a fixed amount (IDR 10 million[7]) to cover losses caused by a flood event associated with the river water height crossing a certain threshold (predetermined trigger)[8] corresponding to a particular floodgate station[9]. The hypothetical product was designed in a way that payouts and perils are covered in the area related to the reference floodgate station, but with each station having a different predetermined trigger (flood index levels associated with the river water level). Households were free to express their willingness to pay (or not) for the hypothetical index-based flood insurance product.

The flood indices associated with the river water level relied on 14 reference floodgate stations distributed across the five regions of Jakarta: eight are located within the megacity, and six are at territory borders (see map in Figure 2)[10]. However, six floodgate stations were not included in this study as a result of simple random sampling when conducting the survey. No household surrounding these six floodgate stations were chosen to be surveyed.

The degree of basis risk associated with the hypothetical index-based flood insurance is measured by using distance of a house to the reference floodgate station (as a proxy). The survey dataset provides the geographic location of households in the study area (x-and-y coordinates expressed as longitude and latitude) [11], whereas locations for existing floodgate

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7 It represents the average maximum amount spent to cover household losses such as housing repairs, clean-up costs, and income loss when flooding occurs. This information was obtained from focus group discussions involving people who live in some flood-prone communities in Jakarta.

8 The thresholds at which payouts are triggered vary from 200 to 950 cm.

9 Each floodgate station has a particular river water level that was determined by the observed measurement during the 2007 flood event in Jakarta. This is known as the critical level of *Siaga 1* (highest alert).

10 Flood indices consider water level information from fluvial, pluvial and coastal flooding in Jakarta. Floodgate stations record river water levels that are identified with flood heights measured in neighbourhoods affected by any type of this natural hazard.

11 There are 81 pairs of missing coordinates in the data due to problems with GPS signal during the survey. Information on household location at the *Rukun Warga* level (Community Unit) and the x-y coordinates of the centroid of these community units obtained from OpenStreetMap website are available for this study. By using these sources of information, we fill in the missing values on coordinates.

stations used as reference stations to trigger payouts were obtained freely from the *Posko Banjir Online* (Flood Information Center Online) website[12].

Surveyed households were referenced to a closer floodgate station if they were downstream from that floodgate station in a particular river; or to a unique, nearest floodgate station in a particular area. We argue that we have introduced sufficient exogenous variation in the degree of basis risk associated with the hypothetical index-based flood insurance product in our estimated model.

Additionally, we offered random variation in monthly premiums among surveyed households. First, they were randomly offered 1 of 5 different premiums[13] to measure their willingness to purchase. Then, if a household did not choose to purchase the index-based insurance product, it received a price discount of 50 percent; otherwise, it faced a price increase of 50 percent. This method follows the double-bounded dichotomous choice contingent valuation (Hanemann et al., 1991) that improves efficiency over discrete choice models. This hypothetical insurance product, however, was priced at a particular actuarially (un)fair price.

Finally, a Binswanger-style lottery choice model (Binswanger, 1980) was utilised in our experiment to measure individual risk preferences and understand how each respondent makes decisions[14]. Table A.1 in the Appendix reports that the tendency of participants to move to a riskier option could have been driven by the fact they were trying to win as much

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12 The information about geographical location of each floodgate station used in this study is available at: http://poskobanjirdsda.jakarta.go.id/map_fullscreen.aspx.

13 The randomised monthly prices chosen were IDR 10,000, IDR 50,000, IDR 100,000, IDR 200,000 and IDR 500,000. The base price was obtained from focus group discussions involving people from some flood-prone communities in Jakarta before conducting the survey. These communities have the "Community Flood Savings" which consists of collecting IDR 10,000 monthly per household in a particular community and uses the saved amount to help affected households during flooding.

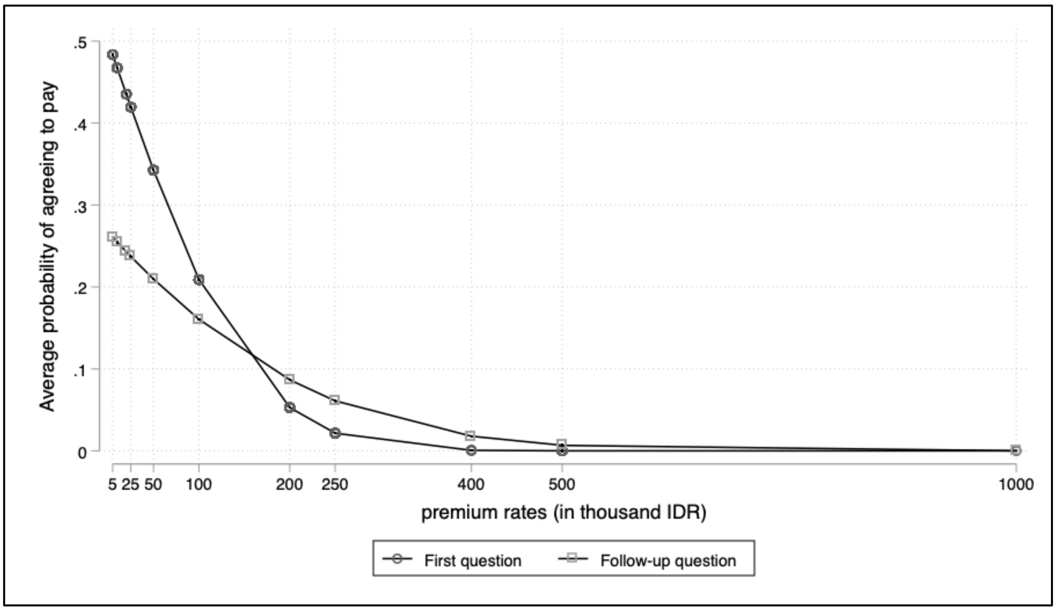
14 This model included two rounds, hypothetical payments and real payments. Under the game, each respondent chooses one of six investment options. These include IDR 20,000 - IDR 20,000; IDR 16,000 - IDR 25,000; IDR 12,000 - IDR 30,000; IDR 8,000 - IDR 35,000; IDR 4,000 – IDR 40,000; and IDR 0 - IDR 50,000. Then, a 'which-hand-is-it in' type game is played with two marbles (blue and yellow), with a probability of 50 percent to yield a return. The respondents are asked to choose a hand. Finally, respondents receive the payment associated with the blue or yellow marble.

cash as possible, rather than revealing a true preference for risk. Therefore, in this study, we present estimates for the relationship between risk aversion (measured through a hypothetical lottery survey) and demand for index-based flood insurance. This is explained by two factors. Firstly, risk preference measures under hypothetical payoffs are consistent with the expected utility theory. Secondly, we do not see significant differences in estimates when we replicate these results using monetary payoffs. Table 1 presents the summary statistics of the households in our survey and the weather-related variables for our analysis.

Table 1. Summary statistics

	(1) Households almost never flooded (258 obs.)		(2) Households occasionally flooded (289 obs.)		(3) Households always flooded (289 obs.)		(4) All households (836 obs.)	
	mean	sd	mean	sd	mean	sd	mean	sd
Panel A: Geographic characteristics								
Distance to closest floodgate station (km)	8.524	6.468	7.830	4.313	12.274	3.590	9.580	5.259
Distance to nearest river (km)	1.328	0.834	1.018	0.843	0.568	0.407	0.958	0.783
Elevation (metres above sea level)	16.194	13.746	19.691	18.363	17.409	8.573	17.823	14.209
Panel B: Premium rates								
First question	153.411	145.901	157.993	156.787	146.747	148.026	152.691	150.367
Follow-up question	91.647	95.371	94.464	84.086	91.851	97.363	92.691	92.246
Panel C: Household head risk preference								
Extreme risk aversion (hypo. lottery)	0.318	0.467	0.291	0.455	0.311	0.464	0.306	0.461
Extreme risk aversion (real lottery)	0.291	0.455	0.294	0.456	0.277	0.448	0.287	0.453
Panel D: Household characteristics								
Household members	3.702	1.392	3.709	1.431	3.668	1.605	3.693	1.480
Age	49.651	10.886	50.851	12.074	51.035	12.105	50.544	11.733
Education	10.318	3.051	9.471	3.480	9.603	3.209	9.778	3.275
Female (1,0)	0.209	0.408	0.183	0.388	0.183	0.388	0.191	0.394
Married (1,0)	0.806	0.396	0.813	0.390	0.803	0.399	0.807	0.395
Income (million IDR)	5.300	3.495	5.234	3.007	4.356	2.870	4.950	3.148
Expenditure (million IDR)	3.769	2.468	3.468	1.860	3.121	1.581	3.441	2.000
House value (million IDR)	15.578	11.235	16.588	15.279	12.357	6.495	14.812	11.717
Homeowner (1,0)	0.764	0.426	0.772	0.421	0.799	0.401	0.779	0.415
Panel E: Weather and flood experience								
Rainfall in 2015 (mm)	1,705.50	126.23	1,715.22	160.04	1,677.68	109.84	1,699.25	134.76
Flood expenses in 2017 (million IDR)	0.272	1.368	0.211	0.363	0.424	1.084	0.303	1.017
Flood shocks	4.109	3.164	4.536	2.918	8.581	2.183	5.803	3.432
Panel F: Perception of flood								
Flood risk (1,0)	0.756	0.430	0.803	0.399	0.782	0.414	0.781	0.414
Flood cycle - every 5 years (1,0)	0.581	0.494	0.599	0.491	0.439	0.497	0.538	0.499
Panel G: Mitigation strategy								
Mitigation (1,0)	0.326	0.470	0.304	0.461	0.356	0.480	0.329	0.470

Figure 3 shows the probability of accepting to buy index-based flood insurance at different price levels. As the monthly premium goes up, the probability of insurance purchase declines. Note that the average monthly premium for households willing to purchase this insurance product is IDR 50,000. Thus, in this study we expect this premium rate to be the actuarially-fair price of the hypothetical index-based flood insurance offered to households.



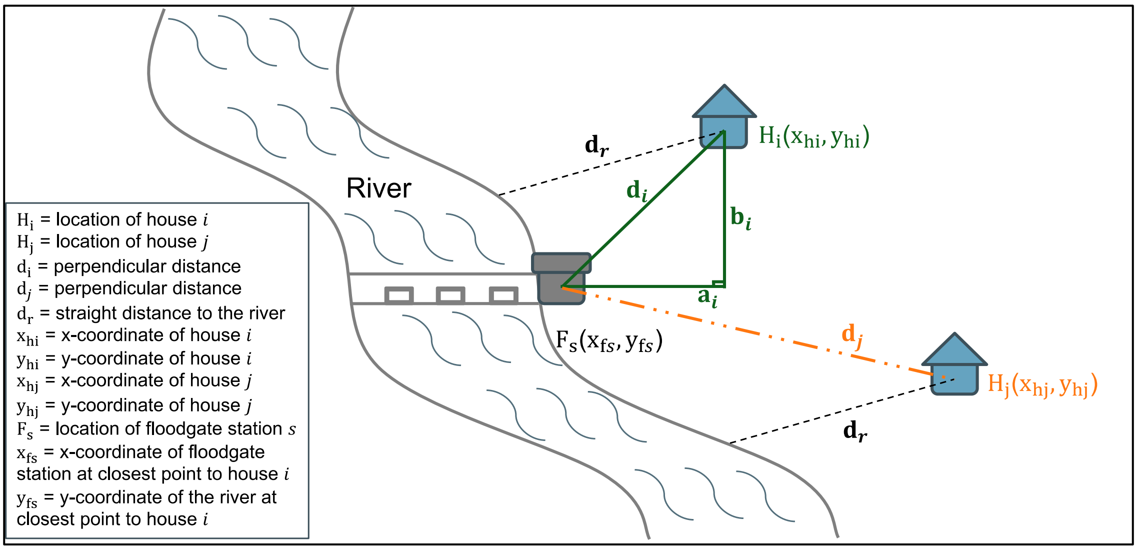
Notes: This figure shows the probability of insurance purchase for the first question and the follow-up question under a dichotomous choice method.
Source: The Impact of Jakarta Floods Survey (2018).

Figure 3. Probability for accepting index-based flood insurance by different price levels

4. Identification strategy

This study takes inspiration from Hill et al. (2016) who used distance to the reference station, premium rates, and household risk aversion in a field experiment to explore the predictions of an expected utility model on insurance demand. As a proxy for basis risk, we use the distance of a house to the reference floodgate station and assume it is exogenous after we control for distance of a house to the nearest river. Households' decision on where to live either far from or closer to the river, is mainly driven by income and amenities, such as affordable housing and adequate basic services[15]. By contrast, distance to the floodgate station is typically ignored[16].

Figure 4 illustrates the spatial proximities, that is, the distance (d_i) of house i (H_i) to the reference floodgate station (F_s), and the distance to the nearest river (d_r). The former is the perpendicular distance to the floodgate station and differences in x-and-y coordinates (a_i and b_i, respectively) to the floodgate station. The latter is the straight-line distance between each sampled household and the nearest river.



Source: Author's own illustration.

Figure 4. Illustration of spatial proximity

In addition, in Figure 4, the distance d_i of house H_i to the reference floodgate station F_s is shorter than the distance d_j of house H_j to the same floodgate station F_s[17] where flood indices are measured for both houses, despite the fact that H_j would potentially experience different flood conditions compared to H_i. This creates basis risk where H_j may not receive

[15] For example, low-income families are often located in densely populated areas that are more likely exposed to flood risks (Jha et al., 2012). In the case of Jakarta, many of the poor have developed large informal settlements along the waterways and rivers (Texier, 2008).

[16] If distance to the station had an impact on location decision-making, households would have considered purchasing coverage to protect their property from flooding; however, as identified in the survey, no households have house insurance.

[17] This means that when a house is closer to a floodgate station, the policy is aligned to the flood information nearby (flood height and damage); whereas when a house is further from a floodgate station, the policy is still aligned to the floodgate station information but not local conditions.

compensation even though they experience losses from flooding, simply due to the fact that the floodgate station records a different level of flooding (e.g., lower). Therefore, the key identifying assumption is that index-based flood insurance demand is negatively affected by the distance to the reference floodgate station, given that distance to the river is controlled in the estimated model[18].

In relation to premium rates, one of five price levels were randomly presented to each respondent for the hypothetical index-based flood insurance product. In theory, each sampled individual had an equal probability of being assigned any of these prices. Then, exogenous variation in the price was introduced by randomly allocating a price discount or price increase across urban households, under a double-bounded dichotomous choice. We test this exogeneity by performing balance tests on a number of covariates. Therefore, the identification strategy used in the study assumes the premium rates have no statistically significant effect on these covariates.

Referring to risk aversion, index-based insurance literature has treated risk preferences as exogenous using Binswanger's (1980) lottery choices[19] in field experiments to infer the levels of risk. Recent empirical research has found that risk aversion may be influenced by natural shocks, including flooding (Chuang and Schechter, 2015; Schildberg-Hörisch, 2018); however, in our experiment, using data of household risk aversion and flood shocks, we find no statistically significant relationship.

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[18] A concern for the credibility of this assumption is that floodgate stations may have been constructed in specific locations based on potential flood risks. In practice, between late 1800 and 1945, the Dutch administration installed floodgate stations at randomly-chosen locations as a part of the drainage system within the Ciliwung river basin and main drains, to control both the flow of water from upstream, and the volume of water entering Batavia – the former colonial port from where Jakarta has expanded.

[19] Each respondent chooses one lottery (investment option) out of six, and a 'which-hand-is-it in' type game with two marbles (blue and yellow) is played. Then, respondents are asked to pick the hand with the blue marble or with the yellow marble (each with a probability of 50%), and the respondent receives the payment accordingly. The investment options are: 1) IDR 20,000 (blue)-IDR 20,000 (Yellow); 2) IDR 16,000-IDR 25,000; 3) IDR 12,000-IDR 30,000; 4) IDR 8,000-IDR 35,000; 5) IDR 4,000-IDR 40,000; and 6) IDR 0-IDR 50,000.

In the estimated model, furthermore, we include region characteristics and flood intensity fixed effects, so that the identifying variations do not disproportionately rely only on flood-prone villages where the impact of flooding is larger. Finally, we account for the variation of flood levels between 2013 and 2017 within a particular village area by calculating the monthly flood shocks[20]. This controls any weather-related influence such as floods on the household decision to purchase index-based flood insurance.

Table 2. Balance test for covariates

Explanatory variable: \ Dependent variable:	Number of household members (1)	Age (2)	Years of education (3)	Female=1 (4)	Married=1 (5)	Income (6)	Expenditure (7)	House value (million IDR) (8)	Own house=1 (9)	Flood-related expenses 2017 (million IDR) (10)
Distance to floodgate station (km)	-0.0158	0.1335	-0.0141	-0.0106***	0.0036	-0.0668***	-0.0457***	-0.3543***	-0.0026	0.0016
	(0.0111)	(0.1074)	(0.0232)	(0.0035)	(0.0034)	(0.0217)	(0.0176)	(0.0713)	(0.0031)	(0.0053)
Premium	0.0002	-0.0032	-0.00003	-0.00001	0.00001	0.0001	-0.0005	0.0004	-0.00004	0.0002
	(0.0002)	(0.0020)	(0.0006)	(0.0001)	(0.0001)	(0.0006)	(0.0003)	(0.0022)	(0.0001)	(0.0002)
Extreme risk aversion (1,0)	0.1196	-0.8551	0.0167	-0.0582*	0.0220	-0.1631	-0.0789	-0.7757	-0.0287	-0.0661
	(0.1165)	(0.9324)	(0.2506)	(0.0308)	(0.0310)	(0.2192)	(0.1574)	(0.6870)	(0.0293)	(0.0467)
Distance to nearest river	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Flood intensity fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: OLS and probit regression estimates for continuous and dummy variables, respectively. Each result represents a regression of the dependent variable on an explanatory variable (which are our study variables). Each result display the coefficients related to each exogenous variable and the bootstrapped standard errors in parenthesis (100 replications). Each regression includes distance to nearest river and fixed effects (region and flood intensity). The number of observations is 836, except for the premium explanatory variable that corresponds to two successive questions, which have 1,672 observations. Asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10 percent, 5 percent, and 1 percent, respectively.
Source: The Impact of Jakarta Floods Survey (2018) and Posko Banjir Online.

Our identification strategy relies on the exogeneity of distance to the reference floodgate station, premium rates, and extreme risk aversion with respect to household characteristics. We test this assumption by performing balance tests of these three exogenous variables on a number of observable variables at the household level. Table 2 displays the outcome of these tests. Most covariates are statistically insignificant; although, by random chance, we should expect some variables to be correlated with our study variables. Therefore,

[20] Shocks are relative to the subdistrict level long-run flood in a particular month (they are defined at a monthly definition). The estimation of monthly flood shocks follows the approach of Karadja and Prawitz (2017) (see Appendix Section B for more details about the calculation.

we conclude that both distance to the reference floodgate station and extreme risk aversion variables are relatively exogenous; by contrast, premium is purely exogenous.

5. Empirical model

The cross-sectional equation of interest is:

$$P\left(y_{ij} = 1\right) = F(\beta_0 + \boldsymbol{\beta_1 D_i} + \boldsymbol{\beta_2 P_i} + \boldsymbol{\beta_3 E_i} + \delta G_{ij} + \gamma X_i + \lambda F_i + \phi_r + \theta_j + \varepsilon_{i,j}) \quad (3)$$

where y_{ij} is the household participation in the index-based flood insurance product (a binary variable = 1 if the ith household in the village j is willing to purchase the product and =0 otherwise). $\boldsymbol{D_i}$ indicates the distance of a house to the reference floodgate station expressed in km; $\boldsymbol{P_i}$ captures the premium rates of index-based flood insurance offered to the ith household; $\boldsymbol{E_i}$ represents the extremely risk averse household (a binary variable = 1 if the ith household is the most risk averse and =0 otherwise); G_j is the vector of geographical characteristics in a village; X_i represents the household characteristics; F_i is a vector of flood experience of the ith household; ϕ_r a fixed effect for the five regions; θ_j is the flood intensity fixed effect at village level; and $\varepsilon_{i,j}$ is the random error. To account for the dichotomous nature of our dependent variable, equation (3) will be estimated by using probit regressions.

We also investigate the interaction of distance to the floodgate station with extreme risk aversion, and with premium in separate regressions to identify the channels through which basis risk impacts demand for index-based flood insurance.

6. Main results

In this section we present the results on the impact of basis risk, premium and risk aversion on the demand for index-based flood insurance. The probit estimations of index-based flood insurance demand for "all sample" includes an initial and follow-up bidding questions asked to surveyed households. Additionally, we present separately these estimations for responses to the “first question” and “second question” in order to identify whether or not we face potential problems of sequential bidding experiments influenced by their starting point (Cameron and James, 1987). Finally, we bootstrap all probit regressions to approximate standard errors, confidence intervals, and p-values for test statistics, based on the sample data.

Based on equation (3), in columns (1) through (3) of Table 3, results suggest that demand for index-based flood insurance is negative and statistically significant at 1 percent for distance to the floodgate station and premium, and negative and statistically significant at 10 percent for extremely risk-averse households, as predicted. When using probit regressions for double-bounded dichotomous choice (“all sample”), and separate first and second questions, we find no significant differences in terms of coefficients and significance level. However, through “first” and “second” question specifications, extremely risk averse yields non-significant estimates. Additionally, a 10 percent decrease in price seems to lead to a 1.3 percentage point increase in uptake which, given the effective demand of 9.9 percent, corresponds to a 22 percent increase in demand for this product[21].

We now turn to the relationship between basis risk and extreme risk aversion. Specifically, we expect the extremely risk-averse households to be more likely to purchase the insurance product when they are closer to the reference floodgate station than far away. Although the coefficient of the interaction term in column (4) is not statistically significant, it has the expected sign.

In column (5), we only consider the effects of basis risk and premium. We assume there is different price elasticity of insurance that households face as they move closer (less basis risk) or further (more basis risk) from the reference floodgate station. We test this

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[21] This is calculated with the product of the average marginal effect for the premium (in logs) variable in column (1) of Table 3, that is -0.134, and the natural logarithm transformation of a 10 percent increase in the same variable, which is ln(0.134).

assumption by interacting premium and distance to the floodgate station. We find a strong significance estimate resulting in price elasticity increases the closer the household is to the reference floodgate station.

Table 3. Index-based flood insurance demand among households

	Dependent variable: Index-based flood insurance demand					
Model: Probit	(1) All sample	(2) 1st question	(3) 2nd question	(4) All sample	(5) All sample	(6) Far from and close to station
Distance to floodgate station (km)	-0.013 *** (0.003)	-0.014 *** (0.004)	-0.010 ** (0.004)	-0.012 *** (0.003)	-0.037 *** (0.007)	
Premium (in logs)	-0.134 *** (0.009)	-0.153 *** (0.009)	-0.108 *** (0.014)		-0.194 *** (0.016)	-0.088 *** (0.012)
Extreme risk-aversion (1,0)	-0.034 * (0.020)	-0.024 (0.025)	-0.039 (0.027)	-0.061 (0.047)		
Distance to floodgate station x Extreme risk-aversion (1,0)				0.003 (0.004)		
Distance to floodgate station x Premium (in logs)					0.006 *** (0.002)	
Floodgate station is close (≤ 5km)						0.419 *** (0.095)
Floodgate station is close x Premium (in logs)						-0.087 *** (0.023)
Distance to nearest river	YES	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES
Flood intensity fixed effects	YES	YES	YES	YES	YES	YES
Number of observations	1,658	829	829	1,658	1,658	908

Notes: This table presents probit regression estimations of household-level insurance uptake on distance to the reference floodgate station, premium and extreme risk-aversion. Average marginal effects are reported. All sample corresponds to double-bounded dichotomous choice questions. The "Far from and close to floodgate station'' sample only includes households at a perpendicular distance from their reference floodgate station below 5 km (''close'') or over 12 km (''far''). In columns (4), (5) and (6) probit specifications include the interaction term. All specifications include distance to nearest river, covariates, as well as region and flood intensity fixed effects. Standard errors for the marginal effects are in parentheses. Standard errors are bootstrapped (100 replications). Asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10 percent, 5 percent, and 1 percent, respectively.
Source: The Impact of Jakarta Floods Survey (2018).

As an additional exercise, in column (6) of Table 3, the sample is restricted to only those households located less than 5 km and more than 12 km from their reference floodgate station[22]. We then use an indicator variable that takes the value of one if a household belongs

[22] The idea to restrict the sample comes from the study by Hill et al. (2016) that considers the average distance to the reference station of the treated (5km) and control (10km) villages in India. In the same way, we find the same difference in distance to the station variable where, on average, households that always experience floods are 12km from the reference floodgate station while households that almost never or occasionally

to the first group (less than 5 km), and otherwise zero. Then, doubling the distance of a house to the reference floodgate station reduces insurance demand by 0.9 percentage points.

To verify the robustness of our main results, Panel A of Table 4 reports the Linear Probability Model (+1 LPM) results which are relatively the same in magnitude and signs as in the main estimates[23]. Moreover, we employ the method developed by Oster (2019) to understand whether variation in unobservables could drive our results – especially in the case of a proxy for basis risk. We set the coefficient of proportionality equal to one (δ=1) which suggests that "the observables are at least as important as the unobservables" (Oster, 2019: 195-196) in determining the outcome variable. In addition, we set the value of R^2_{max}, the R^2 from a hypothetical regression of the outcome on basis risk and both observed and unobserved controls, to be equal to $1.3\tilde{R}^2$, where $\tilde{R}^2$is the R^2 from the corresponding regression from Panel A of Table 4. The magnitude of Oster's statistics (see Panel B of Table 4) makes it very unlikely that the results of distance of a house to the floodgate station can be explained by variation in unobservables.

experience floods are 8km from the reference station; therefore, we sample for 5km ("close") and 12km ("far").

[23] This is also true for the risk preferences with real monetary payoffs instead of hypothetical rewards (see Table A.2 in the Appendix).

Table 4. Linear Probability Model (+1 LPM) and Oster tests

Model: Linear Probability Model	(1) All sample	(2) 1st question	(3) 2nd question	(4) All sample	(5) All sample	(6) Far from and close to station
Panel A.	**Dependent variable:** Index-based flood insurance demand					
Distance to floodgate station (km)	-0.012 ***	-0.013 ***	-0.009 ***	-0.011 ***	-0.040 ***	
	(0.002)	(0.003)	(0.003)	(0.003)	(0.009)	
Premium (in logs)	-0.149 ***	-0.186 ***	-0.116 ***		-0.212 ***	-0.099 ***
	(0.009)	(0.011)	(0.015)		(0.018)	(0.014)
Extreme risk-aversion (1,0)	-0.029 *	-0.023	-0.033	-0.056		
	(0.017)	(0.025)	(0.026)	(0.041)		
Distance to floodgate station x Extreme risk-aversion (1,0)				0.002 (0.004)		
Distance to floodgate station x Premium (in logs)					0.007 *** (0.002)	
Floodgate station is close (≤ 5km)						0.478 *** (0.116)
Floodgate station is close x Premium (in logs)						-0.090 *** (0.021)
Distance to nearest river	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects and controls	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,658	829	829	1,658	1,658	908
R-squared	0.208	0.327	0.132	0.056	0.215	0.211
Panel B.	**Oster tests:** Distance to floodgate station (km)					
(1) Oster δ=1 and Rmax=1.3$\tilde{R}$	-0.019	-0.022	-0.016	-0.019	-0.215	-
(2) Oster δ for β1=0	-17.6	-29.14	-14.54	13.187	2.1398	

Panel A presents Linear Probability Model regressions of household-level insurance uptake on distance to the reference floodgate station, premium and extreme risk-aversion. All sample corresponds to double-bounded dichotomous choice questions. The "Far from and close to floodgate station'' sample only includes households at a perpendicular distance from their reference floodgate station below 5 km (''close'') or over 12 km (''far''). In columns (4), (5) and (6) probit specifications include the interaction term. All specifications include distance to nearest river, covariates, as well as region and flood intensity fixed effects. Standard errors are in parentheses. Standard errors are bootstrapped (100 replications). Asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10 percent, 5 percent, and 1 percent, respectively.
Panel B shows the results of the Oster test for the coefficient of basis risk. In row (1), the estimates are relatively similar in magnitude and sign as in the LPM results.
In row (2), a value of $\delta < 1$ means the observed controls are more important than their unobservable counterparts in explaining the effect of basis on index demand.
Source: The Impact of Jakarta Floods Survey (2018).

Furthermore, we first exclude the set of covariates from the estimations. The results in Table 5 show that all point estimates remain significant and relatively similar. This can be interpreted as evidence of structural validity of the probit specification.

Table 5. Excluding covariates

	Dependent variable: Index-based flood insurance demand					
Model: Probit	(1) All sample	(2) 1st question	(3) 2nd question	(4) All sample	(5) All sample	(6) Far from and close to station
Distance to floodgate station (km)	-0.007 ***	-0.007 **	-0.005 *	-0.008 ***	-0.027 ***	
	(0.002)	(0.003)	(0.003)	(0.003)	(0.007)	
Premium (in logs)	-0.133 ***	-0.155 ***	-0.107 ***		-0.183 ***	-0.089 ***
	(0.007)	(0.009)	(0.012)		(0.018)	(0.014)
Extreme risk-aversion (1,0)	-0.048 ***	-0.038	-0.054 **	-0.089 **		
	(0.017)	(0.025)	(0.027)	(0.048)		
Distance to floodgate station x Extreme risk-aversion (1,0)				0.004		
				(0.004)		
Distance to floodgate station x Premium (in logs)					0.005 ***	
					(0.002)	
Floodgate station is close (≤ 5km)						0.316 ***
						(0.109)
Floodgate station is close x Premium (in logs)						-0.075 ***
						(0.027)
Distance to nearest river	YES	YES	YES	YES	YES	YES
Covariates	NO	NO	NO	NO	NO	NO
Region fixed effects	YES	YES	YES	YES	YES	YES
Flood intensity fixed effects	YES	YES	YES	YES	YES	YES
Number of observations	1,672	836	836	1,672	1,672	914

Notes: This table presents probit regression estimations of household-level insurance uptake on distance to the reference floodgate station, premium and extreme risk-aversion, excluding covariates. Average marginal effects are reported. All sample corresponds to double-bounded dichotomous choice questions. In columns (4), (5), and (6) probit specifications include the interaction term. All specifications include distance to nearest river, as well as region and flood intensity fixed effects. Standard errors for the marginal effects are in parentheses. Standard errors are bootstrapped (100 replications). Asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10 percent, 5 percent, and 1 percent, respectively.
Source: The Impact of Jakarta Floods Survey (2018).

Second, we use the available time-series data of floods from BPBD to perform a placebo test for our identification assumption with respect to basis risk. We only use information from villages that experienced flood water levels above 2 metres (m) registered between 2013 and 2017[24]. Then, we use the village centre as the new location for a hypothetical floodgate station. Due to these areas typically suffering from flooding, and

[24] A box plot is used to visually identify outliers within the flood water level data set, defined as points that are located outside the whiskers of the box plot. These points lie on the range of 200cm – 400cm and provide the information of villages that experienced these flood heights.

households associating them with such events, we assume they may tend to think floodgates are also located in those villages[25].

Table 6. Distance to hypothetical floodgate stations located in village centres with flood levels above 2m

	Dependent variable: Indexed flood insurance demand					
Model: Probit	(1) All sample	(2) 1st question	(3) 2nd question	(4) All sample	(5) All sample	(6) Far from and close to station
Distance to hypothetical floodgate station (km)	-0.0002	-0.014 ***	-0.00003	-0.0001	0.009	
	(0.007)	(0.005)	(0.005)	(0.006)	(0.010)	
Premium (in logs)	-0.133 ***	-0.151 ***	-0.105 ***		-0.117 ***	-0.138 ***
	(0.013)	(0.009)	(0.015)		(0.013)	(0.027)
Extreme risk-aversion (1,0)	-0.041 *	-0.026	-0.044	0.001		
	(0.023)	(0.030)	(0.030)	(0.033)		
Distance to floodgate station x Extreme risk-aversion (1,0)				-0.008 *		
				(0.004)		
Distance to floodgate station x Premium (in logs)					-0.003	
					(0.002)	
Floodgate station is close (≤ 5km)						0.074
						(0.133)
Floodgate station is close x Premium (in logs)						0.012
						(0.031)
Distance to nearest river	YES	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES
Flood intensity fixed effects	YES	YES	YES	YES	YES	YES
Number of observations	1,658	829	829	1,658	1,658	1,204

Notes: This table presents probit regressions of index-based flood insurance uptake on distance to the hypothetical floodgate station, premium rates and extreme risk aversion. Average marginal effects are reported. Distance to the hypothetical floodgate station is represented by the distance of a house to the closest area with flood level above 2 metres which is the placebo. In columns (4), (5) and (6) probit specifications include the interaction term. All probit regressions include distance to nearest river, covariates, as well as region and flood intensity fixed effects. Average marginal effects are reported. Standard errors for the marginal effects are in parentheses. Standard errors are bootstrapped (100 replications). Asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10 percent, 5 percent, and 1 percent.
Source: The Impact of Jakarta Floods Survey (2018).

As expected, placebo estimates are non-significant (Table 6), and close to zero as the variation in basis risk is random. This indicates that distance of a house to the reference floodgate station is exogenous and unique with negative effects on index-based flood insurance demand.

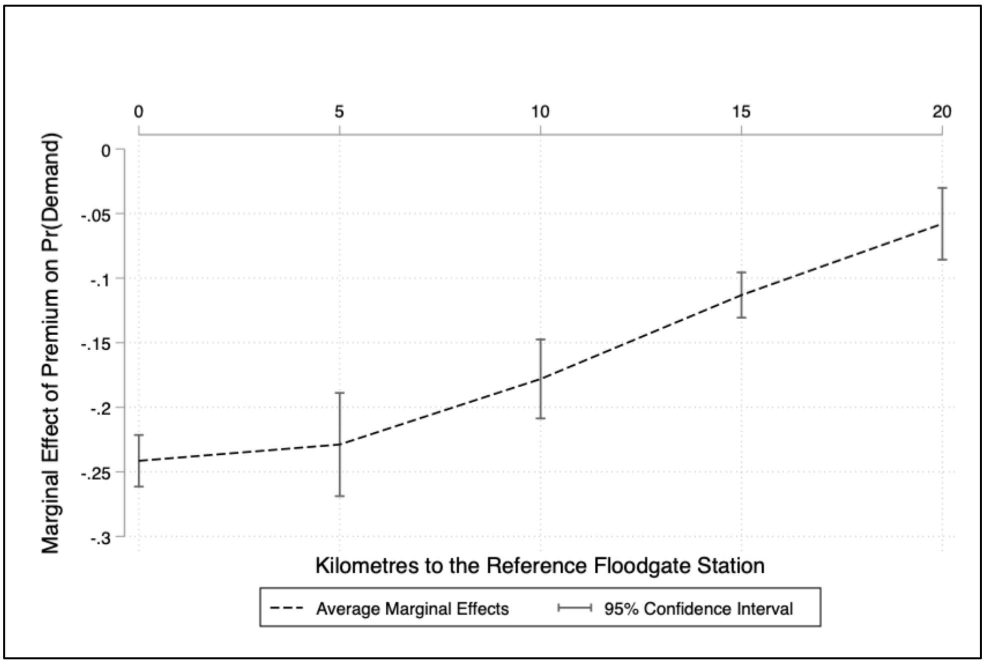
25 Using the OpenStreetMap website to obtain x-y coordinates of the centroid of these villages, we calculated the perpendicular distance of respondents' houses to the hypothetical floodgate station.

Finally, given the sufficient price variation along the hypothetical downward-sloping demand curve, we redo the regression in equation (3) for different levels of premium. Overall, it seems that households who face premiums below IDR 50,000 are more likely to purchase the insurance product; conversely, they are unwilling to buy when the premium is above this value (see Table A.3 in the Appendix).

7. Extended analysis

In this section, we extend our investigation by looking at the heterogeneity of household responses to basis risk, premiums and risk aversion. First, we test whether the index-based flood insurance product demand responds to price changes through different degrees of basis risk. The intuition behind this relationship is: i) when insurance has a low basis risk (close to zero) and is at an actuarially-fair price ($m = 1$), the price elasticity demand is relatively high. This means households are more likely to purchase insurance, particularly if they receive price discounts; and, ii) when insurance has a high basis risk for any amount at or above the actuarially-fair price ($m \geq 1$), the demand price elasticity goes closer towards zero.

Figure 5 shows the average marginal effect of the logarithm of price on the probability of insurance uptake for households located at different distances from the reference floodgate station. Households located less than 5 km from a reference station have a sensitivity to price 4.2 times higher (marginal effect of –0.24) than those located more than 12 km from a floodgate station (marginal effect of –0.06). Based on the above findings, we can conclude that sensitivity to price discounts increase uptake when floodgate stations closer to households are targeted to reduce basis risk. This is an important finding given the potential subsidies (via discounts) on flood insurance contracts.



Notes: This figure shows the relationship between estimated price sensitivity of insurance demand and distance to the reference floodgate station. The dashed line plots average marginal effects of price on insurance uptake, conditional on being located a certain distance from the reference floodgate station. The solid lines plot 95 percent confidence bands around the average marginal effect point estimates. The figure stems from the estimation of a probit regression model of household-level insurance uptake, on variations of prices, distance of the household location to the reference floodgate station, and the interaction between the two excluding covariates. This specification includes distance to nearest river, as well as region and flood intensity fixed effects.
Source: The Impact of Jakarta Floods Survey (2018).

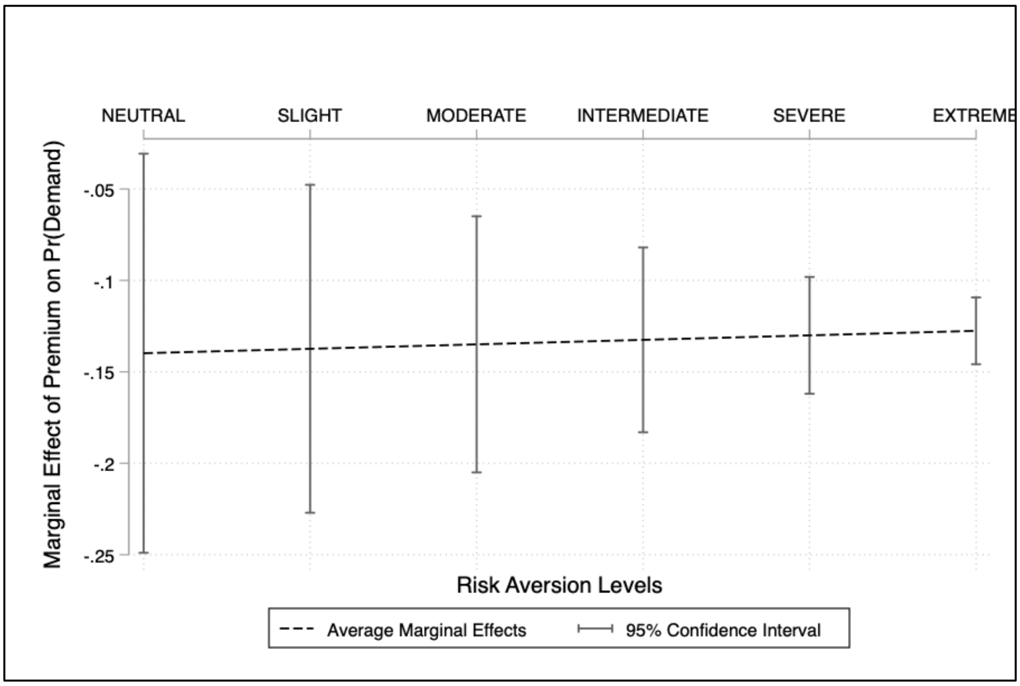
Figure 5. Price sensitivity of demand and distance to reference floodgate station

Second, we look at how the price sensitivity of demand varies across different levels of risk aversion. The Clarke's (2016) model discussed in the theoretical framework section indicates that, in the presence of basis risk ($r > 0$), at different actuarial pricing levels, the insurance demand presents non-monotonic curves in risk aversion. For this reason, we use the following probit specification:

$$P(y_{ij} = 1) = F(\alpha_0 + \alpha_{\mathbf{1}}\boldsymbol{P_i} + \alpha_{\mathbf{2}}\boldsymbol{R_i} + \alpha_{\mathbf{3}}\boldsymbol{P_i} * \boldsymbol{R_i} + \delta G_{ij} + \gamma X_i + \lambda F_i + \phi_r + \theta_j + \varepsilon_{i,j}) \quad (4)$$

where we exclude distance to the reference floodgate station $\boldsymbol{D_i}$ and $\boldsymbol{E_i}$ from equation (3) and introduce $\boldsymbol{R_i}$ which represents the level of risk aversion of ith household, along with the vector of geographical and household characteristics, fixed effects, and random error.

We expect the price elasticity of demand for insurance to be higher among households who are least risk averse than those who are extreme risk averse. We plot the average marginal effect of logarithm of price on the probability of uptake for households with different levels of risk aversion (Figure 6). We observe that least risk averse households have a sensitivity price 1.1 times higher than most risk averse households. Overall, this result appears consistent with the theoretical prediction.



Notes: This figure shows the probability of insurance purchase against different levels of risk aversion. The dashed line plots average marginal effects of price on insurance uptake. The solid lines plot 95 percent confidence bands around the average marginal effect point estimates. The figure stems from the estimation of a probit regression model of household-level insurance uptake, extreme risk aversion, and the interaction between the two excluding covariates. This specification includes distance to nearest river, as well as region and flood intensity fixed effects.
Source: The Impact of Jakarta Floods Survey (2018).

Fig. 6 Probability of insurance purchase across levels of risk aversion

Third, this study examines the price sensitivity of demand in each region[26]. We test the assumption that price sensitivity increases at lower levels of basis risk – i.e., it is higher closer to the floodgate station and lower far away. We observe the point estimates for interaction terms with positive sign and significance levels at 5% and 10% on West and

[26] We exclude Central Jakarta region due to the small number of respondents in the sample (18 households) which would not allow us to regress our probit specification. Also, this region is the least vulnerable from flooding impacts (with an average flood height of 40cm within the 2013-2017 period) due to better flood mitigation infrastructure situated around the city centre.

South regions, respectively, as shown in Table 7. These findings tell us that basis risk is problematic in these two regions. This may be explained by the small number of stations compared to other regions, and the average distance, 7 km and 13 km, between the household and the reference floodgate station. Overall, houses located in the range between 0 km and 5 km seem to estimate the degree of geographical variation in floods and loss occurring at their location as being similar to what may be recorded at the floodgate station.

Table 7. Price sensitivity demand and distance to floodgate station in each region

	Dependent variable: Index-based flood insurance demand			
Model: Probit	(1) West Jakarta All sample	(2) South Jakarta All sample	(3) East Jakarta All sample	(4) North Jakarta All sample
Distance to floodgate station (km)	-0.096 **	-0.013	-0.015	-0.036
	(0.044)	(0.018)	(0.020)	(3.921)
Premium (in logs)	-0.328 ***	-0.237 ***	-0.135 ***	-0.218
	(0.075)	(0.055)	(0.045)	(9.218)
Distance to floodgate station	0.021 **	0.006 *	0.003	0.009
x Premium (in logs)	(0.010)	(0.004)	(0.004)	(0.915)
Distance to nearest river	YES	YES	YES	YES
Covariates	YES	YES	YES	YES
Flood intensity fixed effects	YES	YES	YES	YES
Number of observations	398	474	568	190

Notes: This table presents probit regression estimations of household-level insurance uptake on distance to the reference floodgate station, premium rates and the interaction term (which is the price sensitivity demand). Average marginal effects are reported. All sample corresponds to double-bounded dichotomous choice questions. All columns include distance to nearest river, covariates, as well as flood intensity fixed effects. Standard errors for the marginal effects are in parentheses. Standard errors are bootstrapped (100 replications). Asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10 percent, 5 percent, and 1 percent, respectively.
Source: The Impact of Jakarta Floods Survey (2018).

Fourth, we observe our results by subgroups of income, education level, and flood areas. Columns (1) to (6) in Table 8 show that, in general, results are likely not statistically different among these subgroups. It is clear that premiums are strongly significant in reducing index-based flood insurance demand across subgroups; while distance to floodgate station effects on demand have interesting results. In columns (1) through (4) of Table 8, households with high income and education seem to be slightly sensitive to basis risk compared to those lower in the two categories. This could be due to richer households having a lack of trust for the government to provide index-based flood insurance in Jakarta. Finally, households located in flood zone areas are more sensitive to basis risk and premium. This could be due to the poor usually settling in areas exposed to floods and low amenities, and more sensitive to price changes.

Table 8. Index-based flood insurance demand by subgroup

Model: Probit	Dependent variable: Index-based flood insurance demand											
	(1) Low-income		(2) High-income		(3) Never-attended university		(4) Attended university		(5) Within flood zone		(6) Outside flood zone	
Distance to floodgate station (km)	-0.008	**	-0.015	***	-0.010	**	-0.012	***	-0.019	***	-0.007	*
	(0.004)		(0.005)		(0.004)		(0.004)		(0.005)		(0.004)	
Premium (in logs)	-0.117	***	-0.150	***	-0.137	***	-0.129	***	-0.143	***	-0.112	***
	(0.013)		(0.010)		(0.011)		(0.012)		(0.009)		(0.015)	
Extremely risk-averse (1,0)	-0.078	***	-0.001		-0.044	*	-0.014		-0.039		-0.046	
	(0.029)		(0.028)		(0.026)		(0.029)		(0.027)		(0.037)	
Distance to nearest river	YES		YES		YES		YES		YES		YES	
Covariates	YES		YES		YES		YES		YES		YES	
Region fixed effects	YES		YES		YES		YES		YES		YES	
Flood intensity fixed effects	YES		YES		YES		YES		NO		NO	
Number of observations	826		832		816		842		1,148		510	

Notes: This table presents probit regression of household-level insurance uptake on distance to the reference floodgate station, premium rates and extreme risk aversion. We sample the data set by subgroups relative to the household's income, years of education and whether the household is located within the flood zone. Average marginal effects are reported. All probit regressions include distance to nearest river, covariates, as well as region and flood intensity fixed effects. Standard errors for the marginal effects are in parentheses. Standard errors are bootstrapped (100 replications). Asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10 percent, 5 percent, and 1 percent.
Source: The Impact of Jakarta Floods Survey (2018).

8. Conclusions

This study presents causal evidence on three factors that have effects on the uptake of index-based flood insurance in Jakarta, Indonesia: distance of a house to the reference floodgate station (a proxy of basis risk), premium rates and household risk aversion. We link an expected utility framework developed by Hill et al. (2016), complemented with elements of Clarke's (2016) work, to our empirical analysis to gain a better understanding of index-based flood insurance demand under the presence of basis risk in the urban context.

The results in this article indicate that demand for the index-based flood insurance product offered to urban households decreases as the degree of basis risk and premium increase and declines at higher levels of risk aversion due to the imperfect coverage provided by a product with basis risk. These effects are robust and significant.

In order to design an improved insurance product for the future, it is important to consider the presence of basis risk. Our results find that extremely risk-averse households are more likely to purchase the insurance product when they are closer to the reference floodgate station, i.e., insurance product with lower basis risk. In addition, they verify the price elasticity of demand for insurance is higher when basis risk is low and among households who are less risk averse. Doubling the probability of having basis risk reduces insurance demand by 0.9 percentage points.

The general lessons learned from this study for urban areas in developing countries are as follows. It is important to recognise that the underlying ground station data is generally sparse in developing countries (Dell et al., 2014), and flooding is typically identified as an idiosyncratic local shock. Having enough floodgate stations so as to reduce the degree of basis risk and encourage future demand is key for successfully implementing index-based flood insurance. The rule of thumb concluded from our analysis is that approximately 5 km should be the maximum distance between any house and a floodgate station. If this is not the case, it is integral to invest in the development of new floodgates prior to introducing the insurance product.

In line with the effect on demand of reduced insurance prices, we recommend the application of different levels of premium discounts depending on household location. Our results show that subsidies have an immediate effect on insurance demand, especially households who are offered insurance products with lower basis risk. However, the exact design and structure of a premium discount offering is still unclear in this study due to the unknown nature of household welfare, particularly regarding the level of discount needed to incentivise insurance uptake. This issue presents an opportunity for further research.

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Online Appendix for “Demand for Index-based flood insurance in Jakarta, Indonesia”

by

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Additional tables and figures

Table A.1 Distribution of the degree of risk aversion

Degree of risk aversion		Distribution of sample (percent) when:			
		Hypothetical payoffs were used		Real payoffs were used	
Extreme	IDR 20,000 - IDR 20,000	256	31%	240	29%
Severe	IDR 16,000 IDR 25,000	160	19%	141	17%
Intermediate	IDR 12,000 - IDR 30,000	166	20%	155	19%
Moderate	IDR 8,000 - IDR 35,000	80	10%	79	9%
Slight-to-neutral	IDR 4,000 - IDR 40,000	86	10%	117	14%
Neutral-to-negative	IDR 0 - IDR 50,000	88	11%	104	12%
Total		**836**	**100%**	**836**	**100%**

Source: The Impact of Jakarta Floods Survey (2018).

Table A.2 Index-based flood insurance demand among households with real monetary payoffs

	Dependent variable: Index-based flood insurance demand			
Model: Probit	(1) All sample	(2) 1st question	(3) 2nd question	(4) All sample
Distance to floodgate station (km)	-0.013 ***	-0.014 ***	-0.010 **	-0.014 ***
	(0.002)	(0.004)	(0.004)	(0.004)
Premium (in logs)	-0.134 ***	-0.153 ***	-0.108 ***	
	(0.007)	(0.009)	(0.014)	
Extreme risk-aversion (1,0)	0.018	0.013	0.020	-0.027
	(0.019)	(0.026)	(0.028)	(0.045)
Distance to floodgate station x Extreme risk-aversion (1,0)				0.004
				(0.004)
Distance to floodgate station x Premium (in logs)				
Floodgate station is close (≤ 5km)				
Floodgate station is close x Premium (in logs)				
Distance to nearest river	YES	YES	YES	YES
Covariates	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES
Flood intensity fixed effects	YES	YES	YES	YES
Number of observations	1,658	829	829	1,658

Note: This table presents probit regression estimations of household-level insurance uptake on distance to the reference floodgate station, premium and extreme risk-aversion (with real monetary payoffs). All sample corresponds to double-bounded dichotomous choice questions. The "Far from and close to floodgate station'' sample only includes households at a perpendicular distance from their reference floodgate station below 5 km (''close'') or over 12 km (''far''). In columns (4), (5) and (6) probit specifications include the interaction term. All specifications include distance to nearest river, covariates, as well as region and flood intensity fixed effects. Standard errors for the marginal effects are in parentheses. Standard errors are bootstrapped (100 replications). Asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10 percent, 5 percent, and 1 percent, respectively.
Source: The Impact of Jakarta Floods Survey (2018).

Table A.3 Premium rates and demand for index-based flood insurance

Model: Probit	Dependent variable: Index-based flood insurance demand (1) All sample	(2) 1st question	(3) 2nd question
Premium			
Rp 10,000	0.504 ***		
	(0.094)		
Rp 20,000	0.599 ***		0.640 ***
	(0.086)		(0.079)
Rp 25,000	0.087		0.097
	(0.086)		(0.077)
Rp 50,000	0.123	-0.335 ***	0.082
	(0.081)	(0.064)	(0.078)
Rp 100,000	-0.077	-0.587 ***	-0.047
	(0.081)	(0.057)	(0.070)
Rp 200,000	-0.104	-0.626 ***	-0.012
	(0.083)	(0.054)	(0.096)
Rp 400,000	-0.015		0.029
	(0.127)		(0.141)
Rp 500,000	-0.138 *	-0.657 ***	
	(0.078)	(0.056)	
Rp 1'000,000	0.244		0.333 **
	(0.154)		(0.140)
Distance to floodgate station (km)	-0.011 ***	-0.014 ***	-0.006 *
	(0.003)	(0.003)	(0.003)
Extreme risk aversion (1,0)	-0.036 *	-0.024	-0.042
	(0.020)	(0.027)	(0.031)
Distance to nearest river	YES	YES	YES
Covariates	YES	YES	YES
Region fixed effects	YES	YES	YES
Flood intensity fixed effects	YES	YES	YES
Number of observations	1,549	829	720

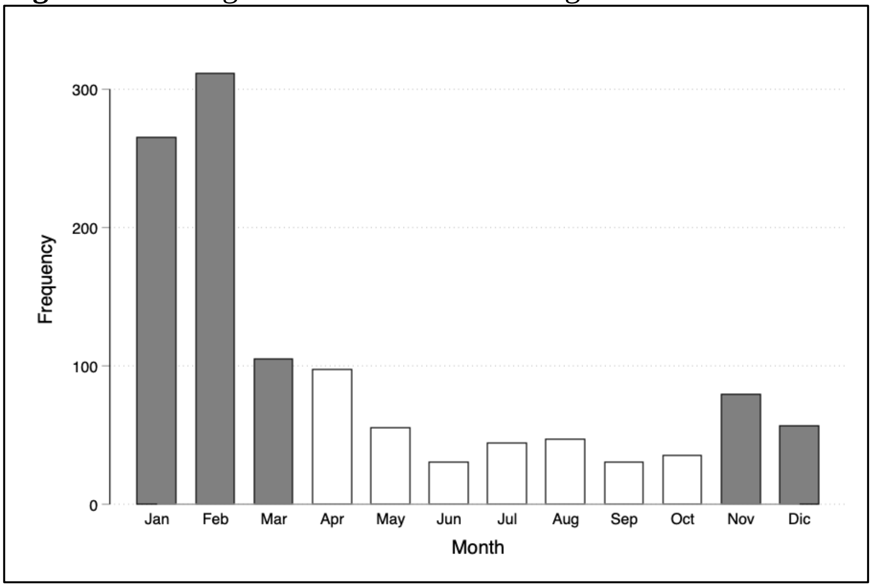
Note: This table displays probit regressions of index-based flood insurance demand on distance to the reference floodgate station, premiums, and extreme risk aversion. Premium rates come from the five price levels and their follow-up (discounted or increased) price under a double-bounded dichotomous choice. All price levels are dummy variables, except for Rp 5,000 which is omitted in the table. Average marginal effects are reported. All sample corresponds to double-bounded dichotomous choice questions. The "far from and close to floodgate station'' includes households at a perpendicular distance from their reference floodgate station below 5km (''close'') or over 12km (''far''). Standard errors for the marginal effects are in parentheses. Standard errors are bootstrapped (100 replications). Asterisk (*), double asterisk (**), and triple asterisk (***) denote variables significant at 10 percent, 5 percent, and 1 percent, respectively.
Source: The impact of Jakarta floods survey 2018.

Estimation of flood shocks[27] in Jakarta

The index-based insurance literature usually employs weather-related shocks as a source of exogenous variation to identify effects associated with insurance coverage. Similarly, in our study we harness the substantial changes in flood levels within a particular spatial unit over a five-year period (2013–2017) in Jakarta, assuming these changes have positive, direct effects on households' willingness to purchase hypothetical index-based flood insurance. If changes in flood levels are not included as a control variable, there may be potential bias in our probit estimates. Such endogeneity concern relies on the idea that some households may be sensitive to flood level variations (i.e. the elderly and pregnant women). Therefore, we measure the variation in flood levels deviations registered at *kecamatan* (subdistrict level) during 5 rainy season months of the 2013-2017 period.

The rainy season brings very intensive rainfall typically between the months of October and April (Texier 2008) and increases the number of flood events in Jakarta; however, most occur from November to March. Figure A.1 shows the number of villages affected by flooding within this period.

Figure A.1 Village flood occurrences during 2013-2017



Source: Jakarta Regional Disaster Management Agency – BPBD (2018).

[27] Flooding data obtained from Jakarta Regional Disaster Management Agency – BPBD. Information was collected in the 2013-2017 period as follows: i) identify the flood areas at village level using GPS devices; ii) at flood locations, depth marks on home walls – water limits of flood depth – were registered as historical data; and iii) ask households for date of previous flooding and time of flooding to recede in their respective neighbourhood. Our data includes 204 villages out of a total of 261.

The estimation of rainy season flood shocks in 2013-2017 follows the approach of Karadja and Prawitz (2017), expressing shocks measured in relation to the local long-run weather in a particular month. First, for each month m, year t and location l, we calculate the deviation between the actual and the long-run average flood level registered in that month:

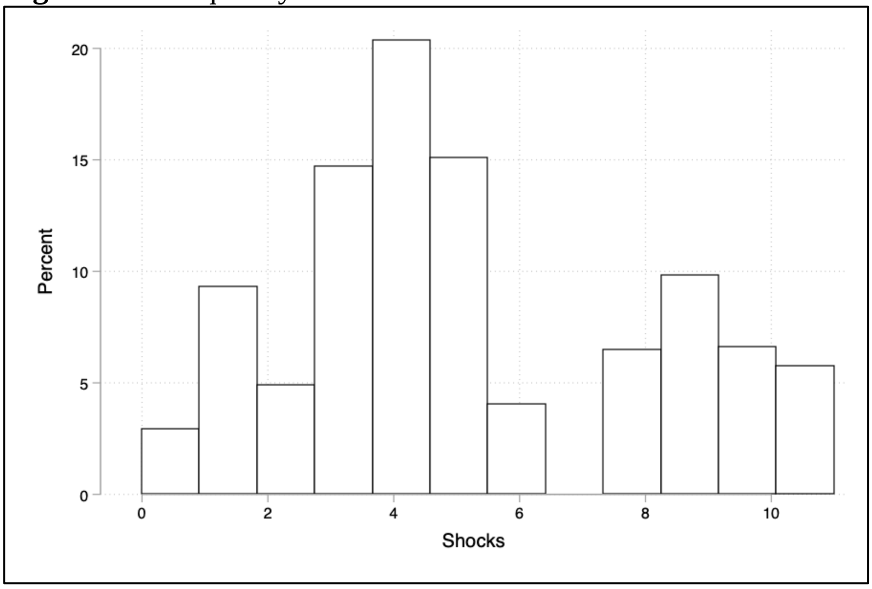
$$deviation\ (Flood\ Level)_{l,m,t} = Flood\ Level_{l,m,t} - \overline{Flood\ Level}_{l,m}$$

where a flood level is the height of flood event occurring in the $kecamatan$. A flood shock is then defined as a binary variable:

$$shock_{l,m,t} \equiv I[deviation\ (Flood\ Level)_{l,m,t} > sd\left(Flood\ Level_{l,m}\right)]$$

where $shock_{l,m,t}$ is equal to one if the $kecamatan\ l$ experienced a positive flood shock in a month m of year t. The $kecamatan$'s long-run standard deviation of flood level in each month over the 2013-2017 period is denoted by $sd\left(Flood\ Level_{l,m}\right)$[28]. Lastly, we sum the number of shocks over the rainy season for each $kecamatan$ between 2013 and 2017. The frequency distribution of flood shocks during 2013-2017 is displayed in Figure A.2, with the median *kecamatan* experiencing four flood shocks. The observations of flood shocks are matched with survey data at subdistrict level.

Figure A.2 Frequency distribution of flood shocks 2013-2017



Source: Jakarta Regional Disaster Management Agency – BPBD (2018).

[28] In order to fill in the missing values (24 observations out of a total of 816), we use that of the nearest kecamatan to complete the long-run standard deviation in a particular month.