Nether Lands

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NETHER LANDS: EVIDENCE ON THE PRICE AND PERCEPTION OF RARE NATURAL DISASTERS

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Abstract
This paper provides evidence on the price and perception of rare natural disasters. We exploit a unique, spatially extremely detailed, dataset on predicted flood water levels in the Netherlands. This dataset, in combination with information on the universe of home sales over the period 1999–2011, allows us to identify people's willingness to pay to avoid flood risk using a border discontinuity design. We find that house prices are on average 1% lower in places that are at risk of flooding. This flood risk discount is more pronounced in neighborhoods with higher predicted flood water levels. Our estimates imply that average perceived flood risk in the Netherlands is much higher than the official protection levels at which the government claims to uphold the country's flood defenses. People expect a flood to happen at least once every 100 years. Depending on the predicted flood water level in their neighborhood, people in flood prone areas are willing to pay 9%–36% more for their flood protection than what the Dutch government currently spends on it. (JEL: D8, Q54, R21)

1. Introduction

Natural disasters carry enormous costs for people living in the affected areas. To mitigate their consequences, governments invest large sums of public money in disaster

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protection, early warning systems and disaster mitigation. It is however notoriously difficult to infer people's willingness to pay for such measures. Of course, one could simply ask people about their willingness to pay to avoid (the consequences of) natural disasters. But, it is extremely difficult to obtain credible results using such a stated preference approach.[1]

Most studies therefore adopt the alternative revealed preference approach. These studies identify people's willingness to pay to avoid natural disaster risk by looking at, notably, the differential in house prices between locations at risk and not at risk of a particular natural disaster. Examples are Bin et al. (2008), MacDonald et al. (1990), or Nakagawa et al. (2007). They all show evidence that natural disaster risk leaves a mark on house prices. However, their identification typically hinges on the strong assumption that their natural disaster risk indicator is exogenous conditional on (linearly) including a, often limited, set of other observable house price determinants.

Other studies exploit the fact that the actual timing of a natural disaster is exogenous, see, for example, Bin and Landry (2013), Troy and Rom (2004), Gallagher (2014), Hallstrom and Smith (2005), Brookshire et al. (1985), Bernknopf et al. (1990), or Naoi et al. (2009). Despite using more credible exogenous variation to identify their effect of interest, these papers are only able to identify how people's perceived natural disaster risk *changes* when a natural disaster hits either their own place of residence, or nearby places. In other words, these studies do convincingly identify how people update their beliefs following a natural disaster, but are unable to identify people's risk perception and/or willingness to pay to avoid these risks per se.

Credible estimates of people's willingness to pay to avoid natural disaster risk are however especially important if one wants to infer people's risk and damage perceptions, or their willingness to pay for (additional) measures to prevent, or mitigate the consequences of, future natural disasters. The main contribution of our paper is in employing a research design that credibly identifies the price and perception of rare natural disasters off exogenous variation in natural disaster risk. Our empirical design rests heavily on the availability of the type of, (spatially) very detailed, data that we are able to use in this paper, but could in principle be used to identify willingness to pay to avoid natural disaster risk in other settings.

We exploit a unique dataset on predicted flood water levels in the Netherlands. For each of the 459,279 six digit postal code (6PPC) areas in the country, the Dutch government provides information on the expected maximum flood water level in case the country's primary flood defenses fail. The median 6PPC area is only 60 m × 60 m, containing 20 houses. In combination with information on the universe of home sales over the period 1999–2011, the quality and spatial detail of this dataset allow us to rely on a border discontinuity type design (BDD) that overcomes many of the difficulties in identifying people's willingness to pay using hedonic valuation methods. In doing so, we relate to earlier applied hedonic papers that identify willingness to pay for other (dis)amenities using credibly exogenous variation (see, e.g., Black 1999; Chay and Greenstone 2005; Greenstone and Gallagher 2008; Gibbons et al. 2013).

1. Three prominent difficulties are: non-response, selected sampling, and the survey priming people into thinking (differently) about natural disaster risk.

To bring our identification of people's willingness to pay as close as possible to the experimental ideal our empirical design exploits the (spatial) detail of our data in three different ways. *First*, we restrict our attention to 6PPC areas containing only attached single family homes (terraced houses). Two randomly selected terraced houses have much more comparable housing characteristics than, for example, two detached houses. *Second*, we base our inference on the variation in house prices and flood risk within the same year and same five digit postal code (5PPC) area. These 5PPC areas have a median size of only 294 m $\times$ 294 m. As such, this step substantially reduces the risk of unobserved, possibly time-varying, neighbor(hood) characteristics confounding our estimated willingness to pay to avoid flood risk. *Finally*, inspired by the border discontinuity design used in notably Black (1999), Bayer et al. (2007), and Gibbons et al. (2013), we first restrict our sample to houses sold in flood safe 6PPC areas that are located within 100 m of a flood prone 6PPC area, and, next, compare house prices in this "control group" to those prevailing in flood prone 6PPCs located within a small distance band of this control group. Basically, we identify willingness to pay to avoid flood risk by comparing house prices in flood prone areas to those prevailing in the very nearest flood safe 6PPCs. It further increases the likelihood of comparing homes that are, apart from their flood risk, equal in all other respects.

Using the previously outlined empirical strategy, we find that house prices are on average *1% lower* in places that are at risk of flooding. Furthermore, this flood risk discount depends systematically on the extent of the flood risk faced: it is higher in places with higher expected flood water levels. By contrast, neither the visibility of water in the neighborhood nor the officially claimed protection level provided by a neighborhood's flood defenses affects people's willingness to pay to avoid flood risk. Also, we show that there is little evidence that either income- or taste-based sorting, or our BDD design's inherent focus on flood prone areas that are nearest to flood safe ground, affects our ability to identify the willingness to pay to avoid flood risk of the average Dutch citizen.

We interpret these results within the confines of a simple hedonic house price model that takes explicit account of the risk associated with living in a flood-prone area (see also Brookshire et al. 1985). Our findings imply that the average Dutch household is not fully confident that the current publicly provided flood protection measures will prevent their property from suffering flood related damages. Despite the country's world class flood defenses, that in the best protected parts of the country are meant to reduce the likelihood of a flood to once every 10,000 years, our estimates imply that people expect a flood to happen at least once every 100 years. Depending on the predicted flood water level in their neighborhood, households are willing to pay between €36 and €146 per year to be fully insured against (the consequences of) future floods. This is 9%–36% more than the current €400 per year that the Dutch government spends on the flood protection of each house at risk of flooding.

Our paper is organized as follows. Section 2 provides a brief overview of the extent of the flood risk and flood protection in the Netherlands. Section 3 details our empirical identification strategy. Section 4 shows our main results. Section 5 interprets these results within the confines our hedonic house price model, and Section 6 concludes.

2. Flood Risk and Flood Protection in the Netherlands

The Netherlands is one of the most flood prone countries in the world. The Dutch have a long history of dealing with the flood risk posed by the sea and rivers that surround them. Today, the country is protected by arguably the world's best flood defenses. The Dutch government spends over €1.1 billion per year on the 3,767 km of dikes and (artificial) dunes and the 1,458 other primary waterworks (dams, weirs, locks, etc.) that protect the country. In the best protected parts of the country they should reduce the likelihood of a flood to once every 10,000 years.[2] Without these defenses, 36% of the Netherlands floods, home to approximately 2.7 million houses/households.

All flood protection is provided publicly. The Dutch government is responsible for upholding the country's flood defenses. And, in case any of the defenses were to fail, the Calamaties and Compensation Act (De Vries 1998) sets out that people should be compensated for flood related damages to their property. However, to what extent, and under which circumstances, the government will compensate such flood related damage is not clearly specified in the Act.[3] All these public flood protection measures are paid from the government's general revenues. It effectively means that the amount that each Dutch citizen pays for the country's flood defenses is *unrelated* to the actual flood risk he/she and his/her property face. On top of this, and very relevant for our analysis, people cannot privately insure their house against flood risk. All private home insurance policies specifically exclude flood related damage from their coverage. The only way to avoid any flood related damage is to move to a house that does not flood even if the country's defenses were to fail.

3. Empirical Identification Strategy

3.1. Underlying Hedonic Model

In this paper we identify people's willingness to pay to avoid flood risk as the log difference in house price between two *otherwise equal* homes, one facing flood risk, the other not.[4] A standard hedonic model extended to incorporate flood risk tells us that this difference, which we denote by α, identifies Dutch average willingness to pay

2. The country's defenses have indeed prevented any major flooding ever since 1953 when the North Sea broke through the dikes and completely flooded the south western part of the country, killing over 1,800 people. In 1995, the Dutch were most prominently reminded of the risk posed by the river-delta they live in. Heavy snow- and rainfall in upstream areas had swelled the main rivers to levels not seen for many decades. 250,000 people were evacuated as some of the country's river defenses were on the verge of giving way. Fortunately, they held up and everyone returned home safely.

3. In 2003, there was a small-scale flood event in a small village called Wilnis, causing about €16 million of damage. Only about half of it was compensated.

4. An interesting anecdote in light of our hedonic analysis comes from Dutch history. The Dutch historian Van der Woude (1972) calculated that houses in the Dutch village of Egmond were worth between 10 and 36 Dutch guilders in 1733. In 1755, they were worthless as a recent flood had moved up the coastline to

(AWTP) to avoid flood risk, expressed in percentage terms. The formal exposition of this model is delegated to Appendix A. Denoting the price of a house as $P(\mathbf{H}, s)$, where $\mathbf{H}$ is a vector of housing attributes and s denotes the centimeters of water entering the house in case of a flood, this AWTP can be written as follows:[5]

$$\alpha \approx \frac{1}{K} \sum_k \left[\underbrace{\rho^k(\tau)}_{\text{perceived flood risk}} \underbrace{[1 - b^k(\bar{s}, \tau)]}_{\text{perceived flood damage}} \overbrace{\left(\frac{\sum_i U^H_{h_i} h_i}{U^X_X} \right)}^{\text{preferences}} / P(\mathbf{H}, 0) \right], \quad (1)$$

where K is the size of the total Dutch population, X denotes non-housing consumption (modeled as one outside good), and h_i denotes the ith housing attribute. From (1) we can immediately see that three different things determine AWTP to avoid flood risk.

First, it depends positively on people's perceived likelihood of a flood happening, $\rho^k(\tau) \in [0,1]$. This likelihood depends negatively on the share of total tax income, τ, that the Dutch government collects to uphold the country's flood defenses. Second, it depends negatively on people's perceived share of the house lost in case a flood does happen,

$$[1 - b^k(\bar{s}, \tau)].$$

Here $b^k(\bar{s}, \tau) \in [0,1]$ denotes individual k's perceived share of each housing attribute surviving a flood with water levels equal to the average expected flood water level in a representative Dutch flood prone area, $\bar{S}$. This share increases in the government's ability to (partly) compensate this damage: $b^k(\bar{s}, \tau)$ depends positively on the share of income that the government collects as "flood tax", τ. Finally, people's AWTP of course also depends on their preferences for each and every housing attribute relative to that for the outside good. Under standard assumptions on people's preferences (see Appendix A), this is captured by the sum of the derivative of their utility function with respect to each individual housing attribute, $U^H_{h_i}$, divided by its derivative with respect to the outside good X, U^X_X.

Equation (1) shows that an insignificant house price differential between houses at risk and not at risk of flooding can mean three different things. People either (i) fully trust the country's public flood defenses so that their perceived flood risk approaches zero: $\rho^k(\tau) = 0\ \forall k$, or (ii) they are confident that the government will fully compensate any future flood damage: $b^k(s, \tau) = 1\ \forall k$, or (iii) they wrongly believe that their house

such an extent that they were now located directly at the sea side. Despite the fact that these houses had not yet suffered from any actual flooding, people were anticipating the consequences of the next flood.

5. The approximation comes from the fact that we include a dichotomous flood risk indicator in our main regressions instead of an actual measure of the cm of water entering the house in case of a flood, s (see Section 3.2). The average willingness to pay of a homeowner to avoid living in an area facing s_1 cm of flood water is the integral of his/her marginal willingness to pay (MWTP) over the interval $[0, s_1]$.

will not incur any damage in case a flood happens: they wrongly believe $s = 0$.[6] By contrast, a positive and significant estimate of α immediately implies that people are not fully confident in the country's flood defenses nor in the ability of the government to fully compensate them for any future flood-related damage. Equation (1) however also clearly shows that it is impossible to separately identify people's flood risk and/or flood damage perception without making further assumptions on people's preferences. In Section 5, we detail the specific assumptions required that allow us to infer people's flood risk and (relative) flood damage perception from our estimates of α.

3.2. *Estimating AWTP to Avoid Flood Risk*

Consistent estimation of people's AWTP to avoid flood risk (or any other housing attribute) is very difficult.[7] There are two main reasons for this. The first is misspecification of the hedonic price schedule, $P(\mathbf{H}, \mathrm{s})$. This could be due to the presence of unobserved determinants of house prices that are correlated with flood risk. For example, areas that have a high risk of flooding may also offer better opportunities for water recreation, or nicer views. Also, the west of the Netherlands is both most at risk of flooding, as well as the country's heavily urbanized economic heartland. But, even if one observes all important house price determinants, an incorrect choice of functional form relating these observed housing attributes to house prices could also lead to biased estimates (see Cropper et al. 1988 for a discussion).

Taste- and/or income based sorting is the second main reason for making it difficult to infer AWTP for a particular housing attribute. People's WTP to avoid flood risk may differ when they have different preferences, different incomes, and/or different flood risk and flood damage perceptions. As a result, different individuals, for example, those with a higher flood risk perception and/or higher incomes, may sort into areas without any flood risk. Income-based sorting makes it more difficult to separate WTP to avoid flood risk from WTP for wealthier neighbors (or characteristics of these neighbors correlated with income). Sorting based on people's flood risk perception and/or risk preferences would instead mean that we are no longer sure that our estimates identify the WTP to avoid flood risk of the average Dutch citizen. Instead, they would represent the AWTP of some non-random sub-sample of the overall Dutch population.

Our main contribution is to address these two issues as credibly as possible using an empirical design that identifies AWTP to avoid flood risk off plausibly exogenous variation only. To do so, we rely heavily on the extreme (spatial) detail of our unique dataset.

6. Another explanation for an insignificant estimate of α would be when people wrongly believe that the likelihood of a flood in the absence of any flood defenses is zero, that is, $\rho^k(0) = 0$. This is extremely unlikely in the Netherlands.

7. See also Gibbons et al. (2013), Black (1999), Chay and Greenstone (2005), or Greenstone and Gallagher (2008) for insightful discussions.

3.3. Empirical Design: Our Flood Risk and House Price Data

We use the most detailed and comprehensive dataset ever compiled on house prices and flood risk. It contains information on officially recorded house prices, various measures of flood risk, and over 130 other possible house price determinants for each of the 459,279 six-digit postal code areas (6PPC-area) in the Netherlands. The median 6PPC covers an area of only 60 m $\times$ 60 m.[8]

For each 6PPC-area we observe the yearly median house price over the period 1999–2011.[9] These medians are based on all property transactions in the Netherlands as registered by *Het Kadaster*. *Het Kadaster* records the exact price of all property transactions in the Netherlands as stated in the official purchase agreement registered at the notary. Each price therefore represents the actual price paid and not the ask-price nor the sometimes different selling price claimed by the broker selling the house. *Het Kadaster* also records the type of property involved in each transaction.[10]

The universal coverage of all property transactions in the *Kadaster* data does result in one minor issue. When people sell part of their residential property (e.g., a piece of their garden, a garage or a boathouse), this is recorded as a property transaction of the same type under which a transaction of the entire property would be listed. It is impossible to distinguish these transactions from the sale of the entire residential property. They result in some unrealistically low "house" prices in the data set. We deal with these observations by excluding those 6PPC areas from our analysis that report a median house price below the 5pct-quantile of all median 6PPC house prices in the same town that the 6PPC is part of.[11] It leaves us with 1,274,629 observations of median 6PPC house prices over our sample period.

Our main flood risk information comes from the website www.risicokaart.nl, the main interactive website of the Dutch government where it informs citizens about

8. The use of aggregate 6PPC level data may induce some biases in the presence of heterogeneity within 6PPC areas in house prices, flood risk and/or other house price determinants (see Chay and Greenstone 2005; Greenstone and Gallagher 2008 that also use aggregated data when estimating a hedonic house price regression). However, we expect any bias, if present, to be small given that the variation in all our variables is typically much smaller within 6PPC areas than between them. In the worst case, our aggregate measure of flood risk at the 6PPC level would hide that the least expensive houses in a 6PPC area classified as facing flood risk are actually located in the safe part of the 6PPC, whereas the most expensive houses in a 6PPC area classified as not at risk are actually located in the flood prone parts of the 6PPC. Such systematic measurement error in our data is very unlikely.

9. If no houses were sold in a particular year, we exclude the 6PPC in that year from the analysis. For a more detailed discussion on the possible selection issues that this may give rise to see Online Appendix B. We also excluded 6PPC-areas from the analysis where non-residential property was sold.

10. It distinguishes six different types of property: non-residential, apartments, detached houses, semi-detached houses (two houses under one roof), terraced houses at the end of a housing block (attached to only one neighboring house), and terraced houses in the middle of a housing block (attached to two neighboring houses).

11. The inclusion of these small scale property transactions introduces additional noise that makes our estimates less precise. We show results using no, or a different correction for these transactions in Online Appendix B.1. Our town definition is those of 2008. There were only minor changes in these definitions over our sample period. On January 1, 2008, there were 443 towns in the Netherlands.

many different types of risks that they and their property face (flood risk, environmental hazards, storage and/or transportation of toxic materials, etc.).[12] Each 6PPC's flood risk is classified into one of seven different flood risk categories that increase in maximum expected flood water levels: no flood risk (0 cm), 0–20 cm, 20–50 cm, 50–80 cm, 80 cm to 2 m, 2–5 m, >5 m. This information is based on flood prediction models developed by Deltares (e.g., Sobek or Delft3D), the leading Dutch institute for applied research in water management. It combines a host of surface characteristics (altitude, natural barriers, etc.), with sophisticated water flow modeling to provide detailed predictions on the maximum water levels reached in each 6PPC in case of a breach in the country's primary flood defenses. See Slager and van der Doef (2014) or Risicokaart (2014) for more detailed descriptions. Figure 1 shows the distribution of flood risk over the country.

In our baseline model, we focus on a dummy variable constructed using this data that takes the value one if the 6PPC area floods in case the primary defenses fail (all the dark areas in Figure 1). We do this as the reported maximum expected flood water level in each 6PPC is measured with more uncertainty than whether or not the 6PPC runs any risk of flooding. The exact flood water levels depend, for example, on the size and type of the breach (see Asselman et al. 2009; Klijn et al. 2010 for detailed discussion on this). Because of this, Deltares simulates hundreds of different flood scenarios, and classifies each 6PPC in one of the previously detailed flood risk categories based on the maximum water level observed in all these different scenarios. Clearly, maximum flood water levels are not the ideal measure of the predicted water levels in case of the most likely flood: the average water level in all scenarios would, for example, do a better job for our purposes. Of course, maximum flood water levels are also not uninformative. We will make extensive use of this data in the most important extensions to our baseline results.

As a second, spatially much less detailed, source of information on flood risk, we collected information on the level at which the government claims to keep up the each 6PPC's primary flood defenses. These defenses are organized in so-called dike-ring areas. Each dike-ring area has an official acceptable flood risk level up to which its defenses should, by law (Water Act 2009), be kept up. Figure B.1 in Online Appendix B illustrates the variation in accepted flood risk between the different dike-rings. Acceptable flood risk levels range from once per 10,000 years for the economic heartland in the western part of the Netherlands, to once per 1,250 years along the main rivers in the east of the country.

Finally, we collected a host of other 6PPC-specific variables that possibly affect house prices and could be correlated to flood risk. They can be distinguished between house and neighborhood characteristics. We either employ these variables as controls in our regressions, or use them to shed light on the possibility of taste- or income-based sorting. Online Appendix C provides further detail on these variables, including a complete list of all 139 variables and their sources.

12. This information is however typically not included in sales listings nor are homeowners required to receive this information at the time of the purchase of a house.

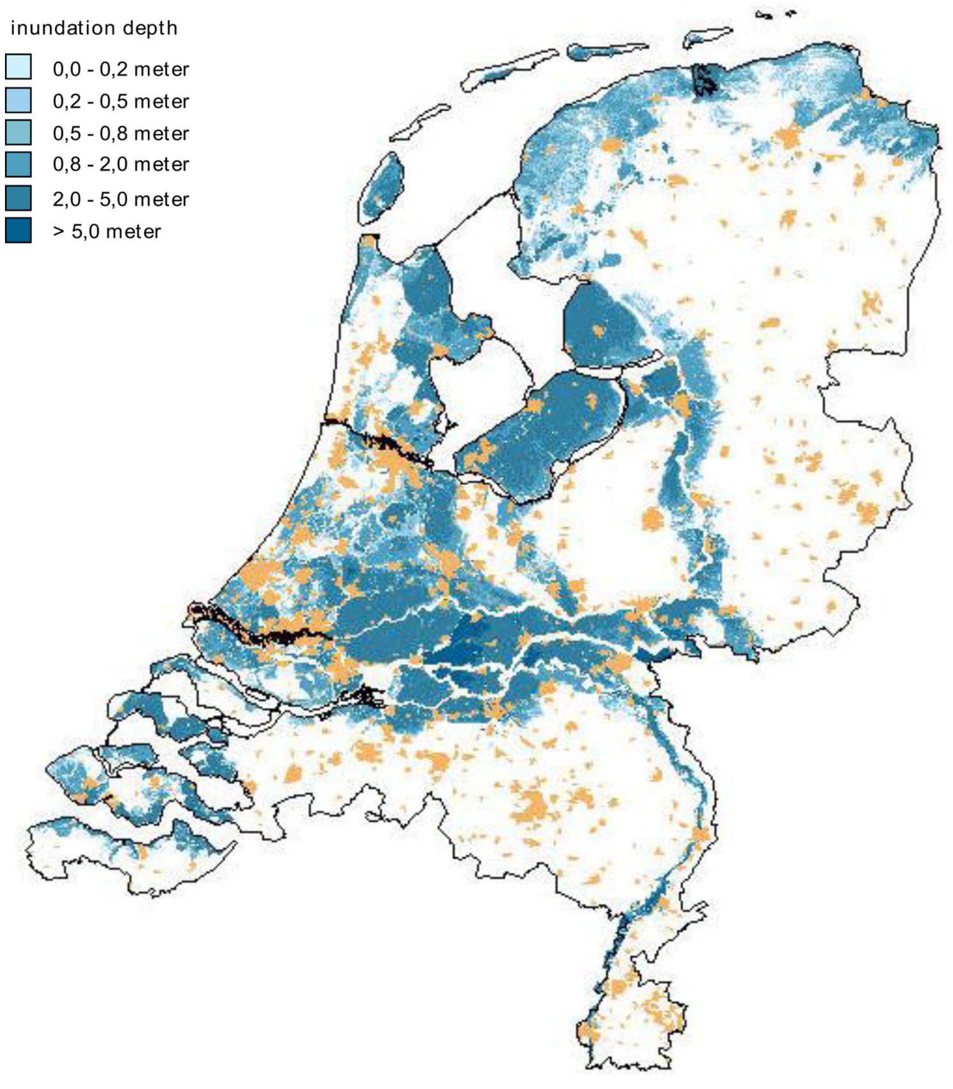

FIGURE 1. Flood risk in the Netherlands. The dark areas in the figure flood in case of a breach in the country's primary sea or river defenses. Darker areas face more flood water. The yellow areas indicate the cities, towns, and villages in the Netherlands.

3.4. Empirical Design: Identification Strategy

Using our dataset, we identify people's AWTP to avoid flood risk, α, using the following simple hedonic regression:

$$\ln P_{ijt} = -\alpha I_i[s_i > 0] + \mathbf{X}_{it}\boldsymbol{\beta} + \varepsilon_{ijt}, \tag{2}$$

where, given that we do not observe individual house prices but the median house price per 6PPC, i from now stands for a 6PPC area. We add subscripts t denoting the year of observation, and j denoting the 5PPC area that the 6PPC area belongs to. $\mathbf{X}_{it}$ contains other determinants of house prices at the 6PPC level that possibly vary over the years, and $\boldsymbol{\beta}$ is a vector capturing the effect of these controls on house prices. $I_i[s_i > 0]$ is our main variable of interest. It is a time invariant dummy variable taking the value 1 if water flows into the 6PPC in case the Dutch primary defenses fail.

Estimating (2), we obtain a consistent estimate of α only if the assignment of houses, and (unobserved) neighborhood characteristics, to flood risk areas is random conditional on the more than 130 observable house price determinants we include in $\mathbf{X}_{it}$. Any remaining unobserved house price determinants correlated with flood risk would still pose a threat to our identification of α. On top of this, any misspecification in the additively linear way in which we control for the other 130 observed house price determinants in (2) could also result in an inconsistent estimate of α. To mitigate these concerns and make our identification as credible as possible, we fully exploit the spatial detail of our data and adopt an empirical design that consists of the following three steps:

First, we restrict our sample to 6PPC areas where only terraced houses, attached single family houses, were sold (*rijtjeshuizen* in Dutch).[13] Terraced houses are the most often sold type of property in the Netherlands. More importantly, two randomly selected terraced houses have much more comparable housing characteristics than say two detached houses, let alone a detached house and an apartment. For example, the standard deviation in m^2 median floor space of houses sold in the same 6PPC area reduces from 44.2 to 28.9 m^2 when considering only terraced houses.[14] Focusing on 6PPC areas with a housing stock consisting exclusively of terraced houses halves our sample to 619,605 observations.[15] This first step does however not yet control for any unobserved neighborhood characteristics affecting house prices that are correlated with flood risk (unless they are perfectly correlated with the likelihood of a 6PPC's housing stock consisting solely of terraced houses).

Steps 2 and 3 of our empirical design aim to do exactly that. As our *second step* we include 5PPC-year fixed effects in (2). That is, we identify α using only the variation in median house prices and flood risk between 6PPCs located in the same 5PPC area, and sold in the same year. The median size of a 5PPC-area is only 294 m $\times$ 294 m. As such, the inclusion of these 5PPC-year fixed effects controls for many, time-varying, neighborhood characteristics, such as the availability of jobs, the quality of public

13. Basically, this selection of terraced houses means that we use a sample of flood and non-flood 6PPC areas that are matched on having the same type of housing stock (see also Black 1999; Gibbons et al. 2013 for a similar (implicit) matching on property type).

14. This reduction is even larger when considering median plot size. There the standard deviation reduces by more than a factor four when only considering 6PPC areas consisting of terraced houses.

15. For comparison, the percentage of 6PPC areas with a housing stock consisting solely of detached houses, two-under-one-roof houses, or apartments is 11.9%, 10.1%, 16.5%, respectively. The other 12.9% are 6PPC areas with a mixed housing stock.

service provision, community taxes, and also, to a large extent, the types of neighbors. Moreover, the terraced houses built in the same 5PPC area are very often identical, so that this step also controls for many of the unobserved characteristics of each house (no. of rooms, size of windows, roof type, etc.). It leaves only very localized, 6PPC-specific, unobservables as possible confounders of our estimated WTP to avoid flood risk. Importantly, 8% of all observations in our terraced house sample (47,308 in total) are in 5PPC areas exhibiting, within the same year of observation, variation in both house prices and flood risk. Figure B.2 in Online Appendix B illustrates this very localized variation in flood risk in case of the city of Dordrecht and its immediate surroundings.

Finally, as the *third step* in our identification strategy, we adopt a border discontinuity type design (BDD). This choice, not to be confused with a regression discontinuity design (RDD),[16] is inspired by earlier contributions of among others Black (1999), Bayer et al. (2007), Ries and Somerville (2010), and Gibbons et al. (2013). In particular, we only take flood safe 6PPC areas that are located within 100 m of a flood prone 6PPC area as our "control group" of flood safe places. Next, we compare house prices in these flood safe "*control 6PPCs*" to those prevailing in flood prone 6PPCs located within a small distance band of the 6PPCs in this control group. Basically, we identify willingness to pay to avoid flood risk by comparing house prices in flood prone areas to those prevailing in the nearest flood safe places. It further increases the likelihood of comparing homes that only differ in terms of their flood risk.

In our baseline estimates we restrict the "*treated 6PPCs*" to flood prone 6PPC areas located within 100 m of a flood safe 6PPC. This choice of distance cutoff is not innocuous. A smaller distance cutoff increases the likelihood of comparing otherwise equal homes, but, at the same time, it also increases the likelihood of obtaining an estimated willingness to pay to avoid flood risk that is no longer representative for houses located deeper into flood prone territory. Strictly speaking, our baseline estimate provides an estimate of the AWTP to avoid flood risk of people living in flood prone 6PPCs located within 100 m from a flood safe area. These 6PPCs make up only 10% of all flood prone 6PPCs. And, although they can be found throughout the Netherlands (see Figure B.3 in Online Appendix B), there are two important reasons why this estimate may not be representative of the WTP to avoid flood risk of the average Dutch citizen.

Both are illustrated by Figure 2 that depicts where the typical sample in our BDD is located relative to the water posing the flood risk. The dike protects an area that

16. A BDD is different from an RDD. The fact that different types of people (or houses) may sort into flood or non-flood prone areas invalidates the crucial assumption underlying any RDD that people have imperfect control over their assignment into treatment or not. See Lee and Lemieux (2010, p. 347) for a detailed discussion of the difficulties arising from the use of geographic borders in an RDD. Our BDD is meant to ensure that we are comparing as similar as possible homes, some of which flood and some do not (e.g., having the same neighborhood characteristics, being similar in type, size, and quality, etc.). We discuss possible issues arising from sorting when interpreting our main findings.

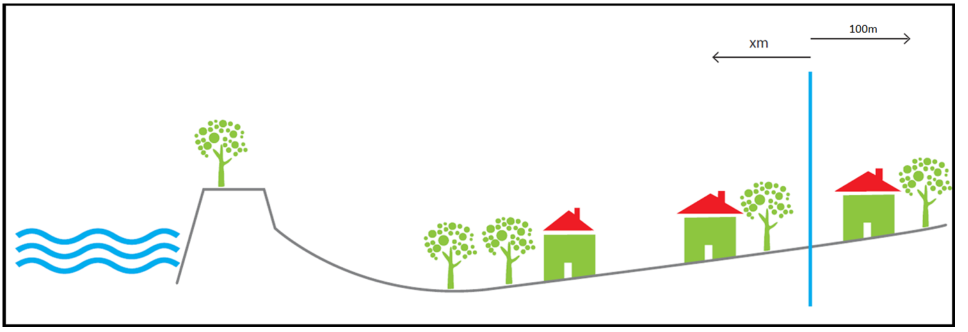

FIGURE 2. Typical location of our “BDD sample”. The vertical blue line in the figure denotes the point where the water will reach in case the area’s primary river or sea defense fails (in the figure this is a dike). Our sample covers all flood safe 6PPC areas within 100 m from this point, as well as all flood prone 6PPC areas within x m from this point. In our baseline results x is set to 100.

extends far into its hinterland. The area immediately surrounding that point where the water reaches in case of a flood, is where we find our “BDD sample”.

The *first* issue is that the extent of the flood risk faced by the average flood prone 6PPC in our baseline “BDD sample” is different from that faced by the average flood prone 6PPC in the Netherlands. Figure 3 shows this in more detail. It depicts, by 100 m distance bands at increasing distance from the nearest flood safe 6PPC, the share of 6PPCs that falls in each of the available expected maximum flood water levels.

Clearly, the share of 6PPCs facing the highest expected flood water levels increases substantially as one moves deeper into flood prone territory.[17] This could mean that our baseline result *under*estimates the AWTP to avoid flood risk. It is however important to note that already 25% of all flood prone 6PPCs in our baseline sample face expected flood water levels of more than 80 cm, and another 10% even more than 2 m. Also, 50%, respectively 75% of all flood prone 6PPCs are located within 400 and 750 m of the nearest flood safe 6PPC.

Second, our selected sample runs the risk of consisting exactly of those flood prone areas whose flood risk is most clearly noticeable. They are located immediately adjacent to flood safe ground. Especially in places where the ground drops steeply (e.g., right next to a dike, immediately behind the dunes, or on a slope leading down to a river plain), it can be very clear which houses do, and which houses do not, run the risk of flooding. Also, the flood prone areas in our selected sample are located closer to the water threatening to flood them. The 10th [25th] percentile distance to the nearest large water body (definitely protected by a dike) of the flood prone 6PPC areas in our “BDD sample” is 465 m [1,392 m] compared to 742 m [1,462 m] for 6PPC areas located beyond 100 m into flood prone territory. In other words, we could be selecting

17. We always group the 2–5 and >5 m categories together since only 0.25% of all observations fall into this latter category.

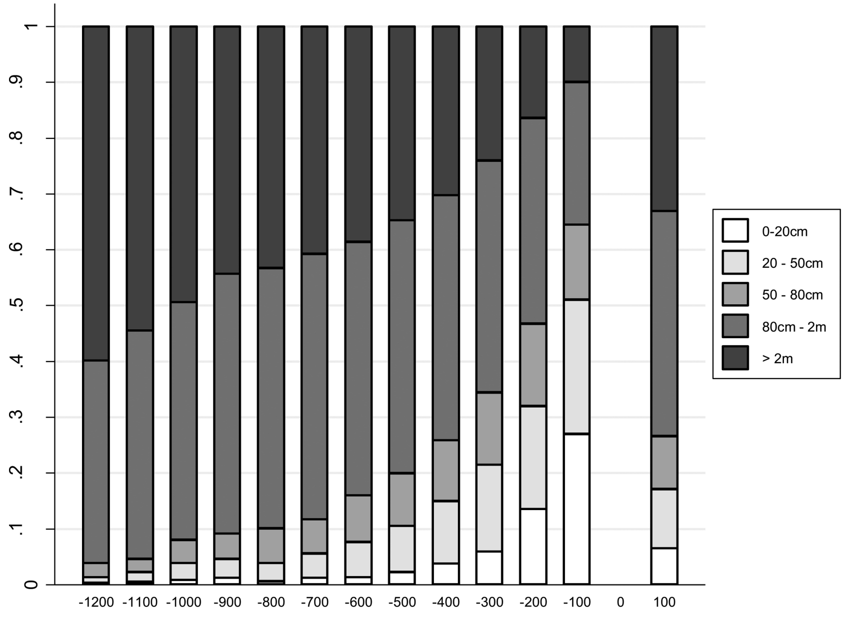

FIGURE 3. Flood depth and distance to the nearest flood safe 6PPC. Each bar is labeled by the endpoint of the 100 m interval it represents. The exception are the bars labeled "−1,200" and "100". The former represents the distribution of the extent of flood risk for all 6PPC areas located more than 1,100 m from the nearest flood safe 6PPC (representing 11.8% of the total number of flood prone 6PPCs). The latter represents the distribution of the extent of flood risk for all flood prone 6PPCs. The percentage of all flood prone 6PPC areas located in each 100 m bin is 9.6% (<100 m), 25.5% (<200 m), 39.1% (<300 m), 50.0% (<400 m), 58.8% (<500 m), 66.4% (<600 m), 72.5% (<700 m), 77.8% (<800 m), 82.0% (<900 m), 85.5% (<1,000 m), 88.2% (<1,100 m).

exactly that sample with the highest chance of finding an effect of flood risk on house prices, leading us to *over*estimate AWTP to avoid flood risk.

In the most important extensions to our baseline results, we will shed crucial perspective on these potential drawbacks of the third step of our empirical design. In particular, we show what happens to our estimate(s) when increasing the distance cutoff used to select the flood prone 6PPCs in our "BDD sample" by 100 m steps until it includes all Dutch flood prone 6PPC areas. And, we will make explicit use of the available information on each 6PPC's maximum expected flood water level in case of a failure of the Dutch primary flood defenses. It allows us to clearly document the trade-off between our empirical design's ability to compare *otherwise equal* houses on the one hand, and our aim of obtaining an estimate of AWTP to avoid flood risk that is representative of the average Dutch citizen on the other hand.

On top of this, we shed light on the possibility of differences in flood awareness among people. Specifically, we allow α in (2) to depend on the visibility of water in the neighborhood and the officially claimed state of the Dutch flood defenses. Furthermore, we probe into the likelihood of income and taste-based sorting and replace the dependent variable in (2) by either household income or, since individual tastes for flood safety are generally unobserved, proxies for households' risk preferences (families with (young) children), and being foreign born (see also Greenstone and Gallagher 2008). The idea is that if people indeed sort into flood safe areas based on one of these observed characteristics, they should be systematically related to flood risk.

4. Results

4.1. Descriptives

We start by showing descriptive statistics of our key flood risk and house price variables. Table 1 shows the mean and standard deviation of these variables for four different

TABLE 1. Descriptive statistics.

	(1) All 6PPC		(2) 6PPC Any house(s) sold		(3) 6PPC Terraced house(s) sold		(4) 6PPC < 100 m flood line Terraced house(s) sold	
	Mean	s.d.	Mean	s.d.	Mean	s.d.	Mean	s.d.
Price (euros)	–	–	231,283	147,827	210,723	100,748	223,828	116,473
No. sold	–	–	1.5	0.9	1.4	0.8	1.4	0.8
Floor space (m^2)	–	–	120	44	116	29	113	31
No. houses	17	12	21	14	20	11	20	11
Flood risk?	0.36	0.48	0.37	0.48	0.42	0.49	0.58	0.49
0–20 cm	0.03	0.17	0.03	0.17	0.03	0.16	0.16	0.36
20–50 cm	0.04	0.20	0.05	0.21	0.04	0.21	0.14	0.35
50–80 cm	0.04	0.20	0.04	0.20	0.04	0.20	0.08	0.27
80 cm to 2 m	0.14	0.34	0.14	0.35	0.17	0.38	0.15	0.36
2–5 m	0.11	0.31	0.11	0.31	0.14	0.34	0.06	0.23
>5 m	0.003	0.05	0.002	0.05	0.003	0.05	0.002	0.04
Elevation (m NAP)	9.1	20.4	8.9	20.5	8.3	20.5	0.8	5.3
Below sea level?	0.26	0.44	0.26	0.44	0.32	0.47	0.51	0.50
Distance to water (m)	582	669	562	642	505	577	284	294
Dist. to large water body (m)	9,982	10,129	9,908	10,080	9,594	9,573	6,698	5,762
Official state of defenses								
Not in dike-ring	0.32	0.47	0.31	0.46	0.28	0.45	0.02	0.15
1/10,000 year	0.27	0.45	0.28	0.45	0.28	0.45	0.49	0.50
1/4,000 year	0.16	0.37	0.16	0.36	0.16	0.36	0.20	0.40
1/2,000 year	0.07	0.25	0.08	0.27	0.09	0.29	0.08	0.27
1/1,250 year	0.17	0.38	0.17	0.38	0.19	0.39	0.20	0.40
1/500 year	0.0001	0.01	0.0001	0.01	0.00003	0.01	–	–
Distance to nearest flood safe/flood prone 6PPC (m)	5,385	9,448	5,194	9,213	4,892	8,975	67	19.7
Observations	5,970,627		1,274,629		619,605		42,998	

Notes: This table shows the mean and standard deviation of the denoted variables for four different samples. Columns (1) and (2) do this for the full sample of all 459,279 6PPC areas (in the 13 years of our sample). Columns (3) and (4) for all 6PPC areas where at least one house was sold. Columns (5) and (6) for all 6PPC areas where only terraced houses were sold. And, finally, columns (7) and (8), do this for 6PPC areas in this terraced house sample located in our baseline "BDD sample" of flood safe 6PPC areas located within 100 meter from a flood prone 6PPC and vice versa.

samples. From left to right, we focus on (1) the *full sample* of all 459,279 6PPC areas (in the 13 years of our sample), (2) 6PPC areas where at least one house was sold, (3) 6PPC areas where only terraced houses were sold, and (4) 6PPC areas in this terraced house sample located in our baseline "BDD sample" of flood safe 6PPC areas located within 100 m from a flood prone 6PPC and vice versa.

Columns (1) and (2) show no substantial differences in flood risk characteristics between 6PPC areas where at least one house was sold and 6PPC areas without any sales. The biggest difference between 6PPC areas with and without any home sales is, not surprisingly, the number of houses within the 6PPC-area.

The difference between 6PPC areas with only terraced house sales and those with at least one house sold are also small when it comes to their flood risk characteristics (compare columns (2) and (3)). The average price paid for a house in the terraced house sample is however about 10% lower than when considering all home sales since detached and "two-under-one-roof" homes are typically sold at higher prices.

Column (4) finally focuses on our baseline "BDD sample". Average house prices, m^2 floor space, and the number of houses sold are very similar to those in the country-wide samples considered in columns (1)–(3). This is not the case for the different flood risk characteristics. Now, about 58% of 6PPC areas are at risk of flooding and 51% located below sea level, compared to around 40% and 30% respectively in the country-wide samples. However, as already shown in Figure 3, expected maximum flood water levels in the flood prone 6PPC areas of our "BDD sample" are smaller than those faced by 6PPC areas located deeper into flood prone territory. Also, virtually all 6PPC areas in our "BDD sample", regardless of whether they flood or not, are located inside one of the Dutch dike-ring areas, compared to only 70% in the three country wide samples.

Next, Table 2 sheds perspective on the ability of our empirical design to balance the observed house price determinants across flood and non-flood prone 6PPC areas.[18] If we do not manage to balance these observables, this would shed doubt on the ability of our design to do so for any possible remaining *un*observable housing attributes. Moreover, if the observable housing attributes are balanced, consistent estimation of the AWTP to avoid flood risk does not depend on the functional form assumptions that we make regarding the relation between these observable attributes and house prices (see Imbens and Rubin 2015).

Table 2 shows the average of different observable housing attributes in 6PPC areas with and without flood risk, also indicating whether they differ significantly from each other.[19]

18. Table B.1 in Online Appendix B complements Table 2. It shows how extending the "*BDD sample*" deeper into flood prone territory affects our ability to balances the observables across flood prone and flood safe 6PPCs.

19. We only show these averages for a subset of all our observable housing attributes. For all other observable housing attributes observed at the 6PPC level that we include as controls in our analysis (see Online Appendix C for a complete list), these descriptives are available upon request. They are all balanced when applying all three steps of our empirical design.

TABLE 2. Balancing on observables across the flood and non-flood prone areas.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Within 5PPC variation only			
Terraced houses	All		"BDD sample"		All		"BDD sample"	
No. of observations	357,640	261,965	17,895	25,103	357,640	261,965	17,895	25,103
	No flood risk	Flood risk	No flood risk	Flood risk	No flood risk	Flood risk	No flood risk	Flood risk
ln median house price	12.17	12.20***	12.25	12.23***	12.18	12.17***	12.24	12.23***
% houses built in:								
<1549	0.04	0.01***	0.10	0.04**	0.04	0.01*	0.1	0.1
1550–1749	0.2	0.1***	0.7	0.4***	0.2	0.02**	0.6	0.5*
1750–1849	0.3	0.2***	1.1	0.6***	0.4	0.02***	0.9	0.7***
1850–1879	0.3	0.3	1.1	0.7***	0.4	0.3	0.9	0.9
1880–1899	1.1	0.9***	1.4	1.7	1.1	0.8***	1.6	1.6
1900–1909	2.1	1.6***	3.3	2.9	2.0	1.7	3.3	3.0
1910–1919	2.2	1.5***	2.4	2.6	1.7	2.1**	2.1	2.8***
1920–1929	4.6	2.8***	4.9	5.4	4.2	3.5***	5.3	5.1
1930–1939	7.4	5.0***	5.6	5.8	6.4	6.3	5.5	5.9
1940–1949	1.8	0.9***	1.8	1.5	1.5	1.4	1.6	1.7
1950–1959	7.5	4.4***	5.0	5.6	6.0	6.5*	5.2	5.4
1960–1969	13.8	12.0***	10.4	12.2***	12.5	13.7***	11.4	11.4
1970–1979	23.1	24.5***	19.8	19.8	23.1	24.5***	19.7	19.9
1980–1989	18.4	22.9***	21.2	20.1	20.6	19.9	20.9	20.3
1990–1999	12.6	17.1***	15.7	15.3	14.6	14.3	15.3	15.6
2000–2011	4.4	5.8***	5.1	5.2	5.1	4.9	5.3	5.1
% monumental houses	0.4	0.2***	1.6	0.9***	0.5	0.1***	1.4	1.1**
ln median floor space (m^2)	4.74	4.71***	4.70	4.69***	4.73	4.72**	4.70	4.69
% monumental building in 6PPC?	1.1	0.6***	2.3	1.7**	1.1	0.6***	2.1	1.8
ln area (m^2)	8.25	8.15***	8.07	8.01***	8.21	8.20	8.06	8.02**
ln built-up area (m^2)	7.14	7.09***	7.07	7.03***	7.13	7.11**	7.05	7.04
Elevation (m NAP)	13.8	0.7***	1.2	0.5***	8.4	8.1***	0.9	0.8***
No. houses	19.6	20.3***	19	19	20	20	19	19
No. inhabitants	51	56***	51	52	53	54*	51	52
% non-western foreign born	1.8	1.9***	1.8	1.9***	1.8	1.8	1.9	1.9
% 0–14 years	20.3	21.6***	20.7	21.0	20.9	20.8	20.8	20.8
% 15–24 years	11.5	11.7***	11.5	11.5	11.6	11.5	11.4	11.6
% 25–44 years	31.7	32.3***	31.7	32.3**	31.9	32.0	32.0	32.1
% 45–64 years	26.2	25.8***	26.9	26.1***	26.1	25.9	26.5	26.4
% 65+	10.4	8.5***	9.2	9.1	9.5	9.8	9.2	9.1
% 1pp households (hh)	23.2	20.3***	22.6	22.1	22.1	21.8	22.4	22.2
% >1pp hh (children)	45.2	49.2***	47.0	47.4	46.9	46.9	47.0	47.3
% >1pp hh (no children)	31.6	30.6***	30.5	30.5	31.0	31.3	30.6	30.5
Mean hh size	2.5	2.7***	2.6	2.6	2.6	2.6	2.6	2.6
Mean hh income rel. to Dutch average	1.04	1.09***	1.12	1.11**	1.06	1.05***	1.12	1.11***
Distance to (m)								
Rail	2,298	2,566***	2,488	2,358*	2,406	2,419***	2,410	2,414*
Road	143	151***	136	139	143	150***	135	140***
Shops/restaurants	814	934***	875	831*	864	865	849	850
Park	469	392***	405	395	437	437	398	400
Public facilities	1,312	1,312	1,233	1,221	1,308	1,317**	1,226	1,225
Recreational area	2,492	2,189***	2,054	2,020	2,366	2,362	2,034	2,035
Agricultural land	503	488***	507	533**	500	492***	523	521

TABLE 2. Continued.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Within 5PPC variation only			
Terraced houses	All		"BDD sample"		All		"BDD sample"	
No. of observations	357,640	261,965	17,895	25,103	357,640	261,965	17,895	25,103
	No flood risk	Flood risk	No flood risk	Flood risk	No flood risk	Flood risk	No flood risk	Flood risk
Forest	944	1,138***	1,241	1,283**	1,025	1,027	1,264	1,267
Open plain (dry)	4,397	7,466***	7,259	8,091***	5,689	5,703***	7,747	7,743
Water bodies								
Open plain (wet)	3,366	2,659***	2,868	2,757**	3,065	3,069	2,804	2,802
Ijssel-/Markermeer	67,466	44,460***	44,363	44,073	57,745	57,731***	44,195	44,192
Estatuary (closed)	68,238	54,246***	50,665	48,305***	62,322	62,321	49,287	49,287
Rhine/Meuse river	31,211	18,413***	24,813	23,084***	25,801	25,799	23,802	23,805
Lake	64,113	45,094***	47,797	48,192	56,077	56,065***	48,029	48,026
Storage/watershed	44,217	26,621***	28,968	26,121***	36,780	36,775	27,307	27,306
Recreational inland waterways	1,798	1,373***	1,357	1,284**	1,622	1,613***	1,315	1,313
Water for nat. resource extraction	14,530	18,055***	19,046	19,422	16,019	16,022	19,264	19,267
Mud flat	21,544	17,792***	17,059	16,656*	19,964	19,949***	16,825	16,823
Other small water	814	372***	370	347***	629	625**	358	356
Waddenzee, Eems, Dollard.	109,826	95,100***	89,732	91,049	103,605	103,593***	90,503	90,499
Oosterschelde	110,661	84,227***	84,716	77,952***	99,488	99,481*	80,767	80,768
Westerschelde	123,219	102,347***	105,019	98,800***	114,396	114,392	101,388	101,389
Noordzee	70,159	47,056***	37,313	34,603***	60,396	60,384***	35,734	35,729

Notes: All numbers reported in the table are averages. The averages in columns (5)–(8) are based on separate regressions of each variable on our flood risk indicator and a full set of 5PPC-year fixed effects. Columns (5) and (7) report the average 5PPC/year fixed effect in these regressions. Columns (6) and (8) instead report the sum of this average 5PPC/year fixed effect and the estimated coefficient on the flood risk indicator. In columns (2), (4), (6), and (8), a *, **, *** is added to averages that are significantly different from that reported for the flood safe 6PPC areas in the same sample at the 10%, 5%, 1% level, respectively. Standard errors are clustered at the 6PPC level.

Columns (1) and (2) compare these averages when considering the full sample of all 6PPC areas in our terraced house sample (i.e., only employing step 1 of our empirical design). It shows that most observables differ significantly between the flood- and non-flood prone 6PPC areas in this sample. Next, columns (3) and (4) focus on our baseline "BDD sample" consisting of all flood safe 6PPC areas within 100 m from a flood prone 6PPC and vice versa (step 3 in our empirical design). And, columns (5) and (6) show how a focus on within 5PPC-year variation only, helps to achieve balance on observables (step 2 in our empirical design). Employing either step individually already substantially reduces the number of significant differences in observables between flood safe and flood prone 6PPCs. However, only when we employ all three steps of our design simultaneously, do we hardly find any remaining significant differences (compare columns (7) and (8)). More importantly, the mean of almost all variables is now virtually identical in the flood prone and flood risk 6PPC areas.[20] Notable remaining (significant) differences between the flood prone and flood safe 6PPCs in our baseline sample are those related to the year the house was built, elevation and household income.[21] We will pay explicit attention to these variables in several robustness checks and extensions (see Section 4.2.1).

Overall, the ability of our empirical design to balance the observables between flood safe and flood prone 6PPCs instils confidence in its ability to also do so for any remaining unobserved house price determinants.

4.2. Baseline Estimates: AWTP to Avoid Flood Risk

Table 3 builds up to our main estimate of the AWTP to avoid flood risk in the Netherlands. It provides crucial perspective on the three ways our empirical design aims to get us as close as possible to identifying our effect of interest off exogenous variation in flood risk only.

In column (1) we simply regress our flood risk indicator on house prices (in logs). This suggests a significant positive effect of flood risk on house prices. This puzzling effect disappears as soon as we control for 113 other possible house price determinants observed at the 6PPC-level (column (2)).[22] They consist of characteristics of the housing stock (year built, m^2 floor space, plot size, etc.), (dis)amenities present in the neighborhood (restaurants, parks, railways, etc.), and, importantly, 28 variables related to the presence of different types of natural, water-related, amenities.[23] We now find a significant negative effect of flood risk on house prices of 1.8%. However, similar to previous papers identifying WTP to avoid flood risk using a hedonic approach (e.g., MacDonald et al. 1990; Bin et al. 2008), this result depends on the strong assumptions that any remaining unobservable house price determinants are uncorrelated with flood risk, and that we specified the correct functional form for the way the observed controls influence house prices.

20. This is important as the lower significance could merely reflect the substantial loss of variation as a result of steps 2 and 3 of our empirical design.

21. Flood prone 6PPC areas are also located significantly further away from a main road or railways. The difference is however about 5 m which is very little compared to an average distance of 140 or 2,414 m to a main road or railway respectively.

22. The fact that the more flood-prone western part of the Netherlands is also its economic heartland is one very important example of a confounder of the positive effect of flood risk on house prices that we find in column (1). Only including province-year fixed effects based on the twelve Dutch provinces already turns the effect flood risk into a negative one.

23. We do not show the estimated coefficients of these controls. They are available upon request. Their sign is typically as expected, especially for the most important (significant) ones (m^2 floor space, plot size, etc.). As house prices need not necessarily vary linearly with distance to a specific amenity, we also always include, besides each distance variable proper, a dummy variable that takes the value 1 if the 6PPC area lies within 25 m of each respective (dis)amenity that we have distance information on. It is based on the idea that location right next to a particular amenity is what matters for people's location decision.

TABLE 3. Baseline results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood risk	0.029***	–0.018***	–0.010***	–0.023***	–0.013***	–0.010***	–0.007**	–0.004***
	[0.002]	[0.002]	[0.003]	[0.008]	[0.004]	[0.003]	[0.003]	[0.001]
House characteristics	No	Yes	No	No	No	Yes	Yes	Yes
6PPC—amenities	No	Yes	No	No	No	Yes	Yes	Yes
6PPC—water	No	Yes	No	No	No	Yes	Yes	Yes
6PPC—neighbors	No	No	No	No	No	No	Yes	Yes
FE	–	–	5PPC/yr	–	5PPC/yr	5PPC/yr	5PPC/yr	–
$<X$ m flood safe 6PPC	–	–	–	<100 m	<100 m	<100 m	<100 m	–
Observations	619,605	616,646	619,605	42,998	42,998	42,760	38,858	563,985

Notes: Standard errors clustered at the 6PPC level in brackets. See Online Appendix C for an overview of all control variables observed at the 6PPC level that we include in our regressions. **Significant at 5%; ***significant at 1%.

Columns (3)–(5) provide evidence on the relevance of the two additional steps of our empirical design aimed at making these assumptions as tenable as possible.[24] In these columns we do not include any observable control variables and solely rely on our empirical design to get an estimate of the effect of flood risk on house prices. In column (3) we identify the effect of flood risk using only the within 5PPC-year variation in house prices and flood risk (step 2 in our empirical design). In column (4) we restrict our sample to flood prone 6PPC areas located within 100 m of the nearest flood safe 6PPC, or vice versa (step 3 in our empirical design). And, in column (5), we employ both these steps. Each step individually already has a similar effect as including our full set of controls, turning the surprising positive effect in column (1) into a flood risk discount. It shows the ability of our design to control for other determinants of house prices correlated to flood risk. Employing both steps of our empirical design, we find a flood risk discount on house prices of 1.3%, significantly lower than the 1.8% discount we found when only including a full set of controls in column (2).

Next, when on top of this including the full set of observable controls, we find a significant negative effect of flood risk on house prices of 1%. Importantly, this point estimate is not significantly different from that when solely relying on both steps in our empirical design in column (5). It gives us confidence that our empirical design is indeed getting us close to the (quasi-) experimental ideal.[25]

24. To also put some perspective on the first step of our empirical design: the point estimate of the flood risk discount decreases to about 0.5% when not restricting the sample to 6PPC areas with a housing stock consisting of terraced houses only (but still employing steps 2 and 3 of our empirical design). Moreover, it is less precisely estimated (but still significant at the 5.2% level), which is not surprising given the much more heterogenous housing stock that we are considering when including sales of all home types to our sample. Results available upon request.

25. Including only our 6PPC controls for 6PPC (dis)amenities, and, those for the presence of different types of natural, water-related, amenities in the 6PPC even leaves the point estimate in column (5) almost unaffected at −0.013. Only when (also) including characteristics of the housing stock does our point estimate change to −0.010. This is not surprising, steps 2 and 3 of our empirical design are best suited to control for neighborhood characteristics.

In this baseline specification we do not explicitly control for any neighbor characteristics (other than by employing steps 2 and 3 in our design). Although they could be important confounders of the effect of flood risk on house prices that we identify, these neighbor characteristics are, in our view, clear examples of "bad controls" (see Angrist and Pischke 2009, pp. 64–66 for a general discussion; see Greenstone and Gallagher 2008; Gibbons et al. 2013 for other examples when estimating hedonic house price regressions). Households choose whether to buy a house at risk or not at risk of flooding. A 6PPC's flood risk status may therefore also determine the characteristics of the households in the 6PPC area, making household characteristics a bad control in a regression of flood risk on house prices. In fact, in many hedonic applications such household characteristics are often excluded from the hedonic house price regression as they are seen as demand shifters, used only when estimating the entire MWTP function (see also Chay and Greenstone 2005 for a discussion). Moreover, the availability of these neighbor characteristics at the 6PPC level is much worse than that of our other variables. It is only available for two years in our sample (we use interpolated data for the missing years), and generally not reported for 6PPC areas that have less than 5 households (see Online Appendix C for more detail). Nevertheless, column (7) shows that our result holds up to also (linearly) adding these 26 "bad controls" to the regression. The effect of flood risk is only slightly lower.[26]

Our baseline estimate shows that people are willing to pay to avoid flood risk despite the public flood defenses in place. The average flood prone house in the Netherlands faces a 1% price discount, about €2400 for the median house at risk of flooding. Before further interpreting this finding in Section 5 using the hedonic model outlined in Appendix A, we first show that it holds up to important robustness checks. And, in Section 4.3, we show that there is little evidence that either income- or taste-based sorting, nor our BDD design's inherent focus on flood prone areas that are nearest to flood safe ground affects our ability to identify AWTP to avoid flood risk. Also, we verify whether our baseline estimate hides systematic heterogeneity in WTP to avoid flood risk related to the extent of the expected flooding or people's flood awareness.

4.2.1. Robustness. Table 4 shows the results of our various robustness checks.[27] First, the fact that our flood risk dummy is a 6PPC specific, time-invariant variable can result in overstating the significance of our estimated flood risk effect. For this reason we always cluster our standard errors at the 6PPC level.[28] An alternative way to deal

26. Note that the difference between a regression with or without these "bad controls" is also much smaller when relying on all steps in our empirical design (compare column (2) vs. (8) to column (6) vs. column (7)). We take it as another indication of the success of our empirical design.

27. Sections B.1 and B.2 of Online Appendix B show additional robustness checks related to sample selection.

28. All results are robust to using standard errors clustered at the 5PPC, 4PPC, or town level instead. The inclusion of 5PPC-year fixed effects in all our main specifications however already controls for most of the spatial dependence in unobservable house price determinants. Moreover, clustering at the 5PPC, 4PPC, or town level reduces the number of clusters used substantially (by a factor 3, 10, or 50 respectively), with possibly unwanted consequences for the reliability of inference (Angrist and Pischke 2009, section 8.2.3). This explains why we report standard errors clustered at the 6PPC level in the main text.

TABLE 4. Robustness checks.

	6PPC averages		1–1 matching	False “Flood line” at +1 m NAP—“Flood Risk” = <1 m NAP	Median 6PPC = 1 sale	Entire 5PPC terraced houses	No “pre-1900” houses	Detailed elevation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood risk	−0.012***	−0.007**	−0.009***	0.002	−0.015***	−0.012***	−0.010***	−0.010***
	[0.004]	[0.004]	[0.003]	[0.011]	[0.003]	[0.004]	[0.003]	[0.003]
House characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6PPC—amenities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6PPC—water	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6PPC—neighbors	–	Yes	–	–	–	–	–	–
FE	5PPC	5PPC	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr
<*X* m flood safe 6PPC	<100 m	<100 m	Nearest only	<100 m	<100 m	<100 m	<100 m	<100 m
No. obs.	9,645	8,980	18,041	13,348	29,543	16,679	38,853	42,760

Notes: Standard errors clustered at the 6PPC level in brackets. Columns (1) and (2) report results of regressing each variable’s average over the 13 years in our sample on average ln house prices over the same period using WLS with the number of years a 6PPC area is observed over our sample 13-year sample period as weights. Standard errors in last two columns are based on robust standard errors. In all columns we focus on the sale of terraced houses only. In column (8) our detailed elevation specification involves including a fourth order polynomial in elevation (measured in m NAP), as well as four different dummy variables indicating whether the 6PPC’s elevation is more than 0.5 m, 1 m, 1.5 m, 2 m higher than the average elevation of all 6PPC areas in the same 5PPC. See Online Appendix C for a detailed description of all control variables observed at the 6PPC level that we include in our regressions. **Significant at 5%; ***significant at 1%.

with this issue (see Angrist and Pischke 2009, p. 313) is to first calculate 6PPC averages of all our variables, and then use these averages to estimate (2) using WLS with the number of years a particular 6PPC is present in our sample as weights. Columns (1) and (2) show that our results hold up to this important robustness check.

In column (3) we match each 6PPC area at risk of flooding to its nearest flood safe counterpart in the same 5PPC area only (instead of using all flood safe 6PPC areas within 100 m from a nearest flood prone 6PPC as our control group).[29] Results when using this even more restricted "matched sample" are very similar to our baseline findings.

In column (4) we show results of a "false experiment". Here we first limit the sample to 6PPC areas facing *absolutely no flood risk*, and then mark those 6PPC areas located below 1 m above sea level as places "*artificially at risk of flooding*". Next, we consider only those 6PPCs located below 1 m above sea level that are located within 100m of a 6PPC located above 1 m above sea level and vice versa, and run our hedonic house price regression (2). A significant "artificial flood risk" effect would shed some doubt on the success of our design. We do not find this to be the case.[30]

Columns (5) and (6) report results when using even more restricted samples of 6PPC areas. Column (5) shows that our baseline findings hold up to only considering 6PPC areas where the median house price reported in a particular year is based on the sale of a single house. As already mentioned in Section 3 (see footnote 8 in particular), our use of aggregate 6PPC-specific measures of house prices and house price determinants could result in issues with measurement error. When the median house price reported for a particular 6PPC is based on a single sale however, this measurement error is confined to the independent variables only. Next, column (6) shows that we find similar results when further restricting our baseline sample to only those "terraced house 6PPC areas" that are located in a "terraced house 5PPC area", that is, 5PPCs whose constituent 6PPCs *all* have a housing stock consisting of terraced houses only.

Finally, columns (7) and (8) take explicit note of the fact that elevation and the presence of houses built before 1900 were two of the important 6PPC specific variables that were not balanced between flood prone and flood safe areas, even when employing all three steps of our empirical design (see Table 2). Houses built before the major defenses were in place are mostly found in places without any flood risk. Many people also find them aesthetically appealing and might therefore pay a higher price for them. If our included "age of the house dummies" do not adequately control for this, this may confound our estimates. Column (7) shows that taking all 6PPC areas with any "pre-1900 houses" out of the sample does not alter our findings in any way. Elevation is clearly related to flood risk, but may also affect the view from the house. Although the average flood prone 6PPC's elevation is only 10 cm below that of the average flood

29. The uneven number of observations in this matched sample is explained by the fact that each 6PPC area may be the nearest 6PPC area with a different flood risk status for more than one other 6PPC area.

30. Similar false experiments using elevation levels of $+2$ m or $+3$ m above sea level show the same result.

safe 6PPC in our baseline sample, one could be worried that our estimated flood risk effect is confounded by the effect of having a nicer view at higher elevation, even after linearly controlling for elevation. Column (8) therefore shows that our results do not change when instead adding a fourth order polynomial in elevation in combination with four different "view dummies" that indicate whether a 6PPC's elevation is more than 0.5, 1, 1.5, or 2 m higher than the average elevation of all 6PPCs in the same 5PPC area.

4.3. Systematic Differences in AWTP to Avoid Flood Risk?

Our results so far provide an estimate of AWTP to avoid flood risk in the Netherlands. Earlier research has however shown that people's flood awareness may differ based on previous flood experience (Hallstrom and Smith 2005; Bin and Landry 2013; Gallagher 2014), on the visibility of the threat in their immediate surroundings, or on the extent of the risk that they and their property face (Troy and Romm 2004). In this section we verify the existence of such systematic differences in WTP to avoid flood risk.

4.3.1. Distance to Flood Safe Ground and the Extent of the Risk. We start with the most important extensions to our baseline results. As discussed in detail in Section 3.4, a drawback of the third step of our empirical design is that our baseline sample only includes 10% of all flood prone 6PPC areas in the Netherlands, that is, those located within 100 m from the nearest flood safe place. And, since expected maximum flood water levels increase as one moves deeper into flood prone territory (see Figure 3), this could very well mean that our baseline estimate is *under*estimating the AWTP to avoid the flood risk faced by the average Dutch flood prone house. Alternatively, it could mean that we are focusing on exactly that sample of flood prone 6PPC areas where the flood risk that people face is most noticeable, possibly leading us to *over*estimate α.

In Table 5(a) we therefore show what happens to our baseline results when we include flood prone 6PPCs to the sample that are located deeper into flood prone territory. Together with Table B.1 in Online Appendix B, that shows how the inclusion of these additional flood prone 6PPCs affects our ability to balance the observables across flood safe and flood prone areas, it puts crucial perspective on the trade-off between our empirical design's ability to compare *otherwise equal* houses on the one hand, and our aim of obtaining an estimate of AWTP to avoid flood risk faced by the average Dutch flood prone house on the other hand.

First of all, Table B.1 in Online Appendix B shows that including flood prone 6PPC beyond 100 m into flood prone territory indeed negatively affects our ability to balance the observables across flood and non-flood prone areas. The difference between flood and non-flood prone places in median m^2 floor space, as well as in the distance to several water related amenities, only disappears in our baseline sample (both in terms of the significance and the size of the difference). The former is particularly noteworthy: as soon as we include flood prone 6PPCs beyond 100 m from the nearest flood safe 6PPC to the sample, we find that the median house in a flood prone 6PPC is 0.7–0.9% smaller than a house in a flood safe 6PPC.

TABLE 5(a). Extending the "treated group" deeper into flood prone territory.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flood risk	−0.010***	−0.009***	−0.008***	−0.008***	−0.008***	−0.009***	−0.009***	−0.009***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
House characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6PPC—amenities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6PPC—water	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr
$<X$ m flood safe 6PPC	<100 m	<200 m	<300 m	<400 m	<500 m	<800 m	<1,000 m	∞
Observations	42,760	84,431	119,674	148,130	171,247	220,725	240,777	278,651
No. with useful within variation	24,599	34,890	38,183	39,148	39,492	39,820	39,896	39,948
% flood prone 6PPC's in sample	10	26	39	50	59	78	85	100
t-stat Hausman		−0.98	−1.85*	−1.95*	−1.84*	−1.54	−1.84*	−1.95*

Notes: Standard errors clustered at the 6PPC level in brackets. The reported Hausman t-statistic in each column is calculated as the difference in the estimated flood risk effect between column (1) and that column, divided by the standard error of that difference. See Online Appendix C for an overview of all control variables observed at the 6PPC level that we include in our regressions. *Significant at 10%; ***significant at 1%.

Table 5(a), where we always (linearly) control for these observable differences between flood and non-flood prone 6PPCs, complements these results by showing that the estimate of people's AWTP to avoid flood risk does not change much when extending our BDD sample deeper into flood prone territory. If anything, our point estimate falls by 0.1 ppt. Results of a simple Hausman test lend support to the usefulness of interpreting these findings: conditional upon all steps of our empirical design, we, if at all, only reject the exogeneity of our flood risk indicator at 10% when extending our "BDD sample" deeper into flood prone territory.[31]

However, we would be too quick to now conclude that our baseline estimate is not *under*- or *over*estimating AWTP to avoid flood risk. The results in Table 5(a) come with one caveat. Although the number of flood prone 6PPCs in the sample increases substantially when moving deeper into flood prone territory, the number of observations providing us with the necessary within 5PPC-year variation does not increase once we go beyond 400 m into flood prone territory. At this point the sample covers about 50% of all flood prone 6PPCs, and the risk profile of a 6PPC is much more in line with that of the average 6PPC (see Figure 3). But, beyond this point, the share of 6PPCs facing maximum expected water levels of more than 2 m becomes larger still, whereas that of 6PPCs facing less than 80 cm of water decrease. In sum, one could remain worried that we are *under*estimating α.

Table 5(b) aims to further alleviate this concern. There, we also take the data on each 6PPC's *maximum expected flood water level* seriously, and estimate AWTP to avoid flood risk separately for each of five different maximum flood water level categories. Importantly, this substantially increases the number of observations that provide us with useful within 5PPC-year variation. Before, all 6PPC areas located in 5PPC areas that flood in their entirety did not provide us with any useful variation. Now, they may do so if their 5PPC area exhibits variation in the extent of the flood risk faced by its constituent 6PPCs. Indeed, the number of observations providing us with the necessary within 5PPC-year variation is substantially larger than when basing our inference on a single flood risk dummy (compare the numbers reported at the bottom of Tables 5(a) and 5(b)). Moreover, the expansion of the number of 6PPCs providing such variation keeps much more pace with the increase in the total number of observations as one includes flood prone 6PPCs at ever further distances from the nearest flood safe 6PPC to the sample.

Interestingly, we find evidence that AWTP to avoid flood risk does depend on the actual extent of the flood risk facing the house: the higher expected maximum flood water levels, the more people are willing to pay to avoid this flood risk. Moreover, the estimated flood risk discount is often not significant in 6PPCs with expected maximum flood water levels up to only 50 cm. Importantly, we find this irrespective of the distance cutoff used for the inclusion of flood prone 6PPCs. Also, a Hausman

31. In addition, Tables B.4a, B.4b, and B.5 in Online Appendix B show results when also extending the *"control group"* of flood safe 6PPC areas to those within 200 m from the nearest flood prone 6PPC. We always reject the exogeneity of our flood risk indicator (in Table B.4a of Online Appendix B), or indicators (in Table B.4b of Online Appendix B), in that case.

TABLE 5(b). Predicted maximum flood water levels and AWTP to avoid flood risk.

Maximum flood depth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0–20 cm	−0.005	−0.005	−0.006*	−0.005	−0.006*	−0.005	−0.005	−0.005
	[0.004]	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
20–50 cm	−0.004	−0.005	−0.005	−0.005	−0.005	−0.007**	−0.007**	−0.007**
	[0.005]	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
50–80 cm	−0.014**	−0.010**	−0.011***	−0.008**	−0.008**	−0.009**	−0.010***	−0.011***
	[0.006]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004	[0.004]	[0.004]
80–200 cm	−0.020***	−0.017***	−0.013***	−0.014***	−0.013***	−0.013***	−0.012***	−0.012***
	[0.005]	[0.004]	[0.004]	[0.004]	[0.003]	[0.003	[0.003]	[0.003]
>200 cm	−0.020**	−0.015**	−0.007	−0.010**	−0.011**	−0.011**	−0.012***	−0.014***
	[0.010]	[0.006]	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.004]
p-value identical?	[0.115]	[0.054]	[0.138]	[0.138]	[0.226]	[0.371]	[0.502]	[0.274]
House characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6PPC—amenities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6PPC—water	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr
$<X$ m flood safe 6PPC	<100 m	<200 m	<300 m	<400 m	<500 m	<800 m	<1,000 m	∞
Observations	42,760	84,431	119,674	148,130	171,247	220,725	240,777	278,651
No. with useful within variation	30,034	54,529	71,827	83,257	91,631	106,605	111,502	119,948
$X^2(5)$-stat Hausman		2.05	5.64	4.95	5.53	5.72	5.84	4.81
% flood prone 6PPC's in sample	10	26	39	50	59	78	85	100

Notes: Standard errors clustered at the 6PPC level in brackets. The reported Hausman $X^2(5)$-statistic in each column tests for the (joint) difference of all 5 flood risk coefficients in each column and those reported in column (1). See Online Appendix C for an overview of all control variables observed at the 6PPC level that we include in our regressions.
*Significant at 10%; **significant at 5%; ***significant at 1%.

test now never rejects the exogeneity of our flood risk indicators when extending our "BDD sample" deeper into flood prone territory. It gives us further confidence that our baseline estimates of people's AWTP to avoid flood risk are also representative for those living in flood prone places beyond 100 m from the nearest flood safe area. If anything, the slightly smaller point estimates when extending the sample deeper into flood prone territory, suggest that people's flood awareness may be larger in flood prone places located closer to flood safe ground.

4.3.2. Awareness. In this section, we further explore possible heterogeneity in people's AWTP to avoid flood risk related to differences in flood awareness. In particular, we verify whether AWTP to avoid flood risk is systematically related to information on the official flood protection levels (claimed to be) upheld by the government, and the visibility of water in the neighborhood. Both can be expected to primarily affect people's perceived likelihood of a flood happening. On top of this, the visibility of water in the neighborhood may also influence people's expected damage in case of a flood. Table 6 shows our results.[32]

First, in column (1), we take locations located in a dike-ring offering the highest protection level (a chance of failing only once every 10,000 years) as benchmark, and verify whether AWTP to avoid flood risk is higher in places located in dike-rings protected by weaker flood defenses (see Figure B.1 in Online Appendix B for the variation in the flood protection levels in each dike-ring area). We find no significant differences in AWTP to avoid flood risk depending on these official risk levels. It implies that people are either unaware of the official protection levels of their flood defenses, or, more likely, they are aware of them but doubt that they accurately reflect reality. In fact, recent analyses of the state of the Dutch primary flood defenses show that the officially claimed protection level of each dike-ring area overstates the actual level of flood protection provided for many of its constituent 6PPCs. 25–50% of the flood defenses were found not to live up to their acclaimed levels of protection (Inspectie Verkeer en Waterstaat 2011). On top of this, the official protection levels were set around 1960 and based on the likelihood of a flood as a result of water levels higher than what the defenses are built for. Since then it has become clear that such overflow constitutes only about 40% of the flood risk, the rest coming from, for example, piping, a dike subsiding or breaking, or the failure of a lock or weir. Taking

32. We also do not find any significant changes in people's WTP to avoid flood risk over the years in our sample period. Moreover, we find no evidence that AWTP to avoid flood risk is different in 6PPC areas that were evacuated during the large-scale near river floods in 1995 (see footnote 2). The interpretation of this finding is not straightforward however, especially since 6PPC data on house prices and flood risk does not exist prior to 1999. It could, for example, mean that people have not updated their flood expectations following the 1995 evacuations. Since no actual flooding happened, the evacuations only reinforced people's trust in their flood defenses. Instead people's flood expectations may have changed immediately after the evacuations, but, four years later, they have reverted back to what they were before 1995 (see Bin and Landry 2013; Gallagher 2014 for evidence of such temporary effects of actual flood events on people's flood expectations). Alternatively, it could also be that people living in these areas at the time of the evacuations have updated their flood expectations, but have sold their homes to unaware people that lived in non-evacuated areas in 1995.

TABLE 6. Differences in flood risk awareness?

Official state of defenses		Visibility of water		
	(1)		(2)	(3)
Flood Risk	−0.008**	Flood risk	−0.009***	−0.008**
(1/10,000 years)	[0.004]		[0.003]	[0.004]
Official state of defenses:		Distance to:	Large water body	Water
1/4,000 years	−0.011	<250 m	−0.001	–
	[0.008]	250–500 m	−0.008	–
1/2,000 years	−0.013	500–750 m	0.013	–
	[0.012]	750–1,000 m	−0.036**	–
1/1,250 years	0.006	1,000–1,250 m	0.007	–
	[0.008]	<30 m	–	−0.013
No dike-ring	0.002	30–60 m	–	0.004
	[0.022]	60–90 m	–	−0.003
		90–120 m	–	−0.010
		120–150 m	–	0.003
p-value equal?	[0.366]	*p*-value equal?	[0.287]	[0.842]
House characteristics	Yes		Yes	Yes
6PPC—amenities	Yes		Yes	Yes
6PPC—water	Yes		Yes	Yes
FE	5PPC/yr		5PPC/yr	5PPC/yr
<*X* m flood safe 6PPC	<100 m		<100 m	<100 m
Median (q25) distance to water (m)			5,859 (1,511)	197 (102)
No. obs.	42,760		42,760	42,760

Notes: Standard errors clustered at the 6PPC level in brackets. Estimated coefficients are for each respective variable *interacted* with the flood risk dummy. See Online Appendix C for a detailed description of all control variables observed at the 6PPC level that we include in our regressions. **Significant at 5%; ***significant at 1%.

these into account results in drastic reductions of the actual protection levels offered by many of the Dutch defenses (see Veiligheid Nederland in Kaart 2014).

In columns (2) and (3), we instead consider possible heterogeneity in people's WTP to avoid flood risk related to the visibility of water in the neighborhood. We do this in two different ways. In column (2), we verify whether WTP to avoid flood risk depends on the distance to a large water body that is visibly protected by the country's primary flood defenses (the sea, and the main rivers and lakes). And, in column (3), we instead consider the distance to any type of water, also including streams, creeks, or ditches that are visible, but not always visibly protected.[33] In both cases, we do not

33. For example, because their water level is kept at acceptable levels by a weir, lock, or pumping station. The distance to any type of water is typically much smaller than that to larger water bodies. It explains why we use different distance bands in each of the two cases.

find any evidence that people living closer to the water that threatens them are more aware of the threat.

4.3.3. Sorting. Finally, we employ the available information on neighbor characteristics to probe into the likelihood of income- and taste-based sorting (see Section 3.2 for an important remark on the quality of this data). Inspired by Greenstone and Gallagher (2008), we look for evidence of sorting by simply replacing the dependent variable in (1) by either household income, or, given that people's preferences for flood safety are generally unobserved,[34] by one of three different proxies of households' flood risk preferences.[35] Two of these proxies, the percentage of households in the 6PPC with children and the percentage of 0–14 year olds in total 6PPC population, are based on the idea that families with young children have a stronger taste for flood-safety. The other proxy, the percentage of non-western foreign born in total 6PPC population, is based on the idea that immigrants might be more or less sensitive to the risk of flooding as they are less accustomed to living with this flood risk. Also, flood risk may be one of the first things people think about when moving to the Netherlands.

Table 7 shows the results of these "sorting-regressions", always employing all three steps in our empirical design. In columns (1)–(4) we do not include other neighbor characteristics as controls. In columns (5)–(8) we do, and we also include a 6PPC's median house price (reflecting the quality of the housing stock) despite the fact that these variables can be argued to be "bad controls" (see the discussion in Section 4.2).

We find some evidence for income-based sorting in column (1). Household income is 0.7% higher in places without any flood risk. This appears to be entirely capitalized into the housing market. Controlling for house prices in column (5), we no longer find any significant effect of flood risk on household income. The wealthier households are the ones that can afford to pay the more expensive houses in these areas.[36] It means that our baseline estimate of AWTP to avoid flood risk might be (partly) picking up WTP to live next to wealthier neighbors. However, Column (7) in Table 3 and column (2) in Table 4 already showed that controlling for household income when estimating (2) only marginally decreases our estimated AWTP to avoid flood risk.

34. Bayer et al. (2007) propose a solution to this issue when individual tastes for the housing attribute of interest vary with observable characteristics of these individuals (e.g., their income, education levels, sex, etc.). If tastes vary for other unobserved reasons, their method would however still not fully address it. Others have proposed a correlated random-coefficient model to deal with this issue (see, e.g., Chay and Greenstone 2005). Their approach relies on the availability of a credible instrument that, in our case, would be correlated with the extent of flood risk facing a 6PPC, but not to any other (unobserved) determinant of median house price in the 6PPC. We lack a credible candidate for such an instrument.

35. As an alternative we also estimated (1) including an interaction term between each of these four neighbor characteristics and our flood risk indicator. None of the interaction terms turned out significant when doing this. Results available upon request.

36. The average Dutch household spends about 24% of its net income on housing (CBS 2012). Only controlling for house prices already turns the effect of flood risk on household income insignificant. Result available upon request.

TABLE 7. Sorting: income and risk preferences.

	ln hh income (1)	% non-western foreign-born (2)	% hh with children (3)	% 0–14 years (4)	ln hh income (5)	% non-western foreign-born (6)	% hh with children (7)	% 0–14 years (8)
Flood risk	−0.007**	0.003	0.506	0.079	−0.003	−0.012	−0.018*	0.014
	[0.003]	[0.021]	[0.338]	[0.167]	[0.003]	[0.021]	[0.011]	[0.015]
House characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6PPC—amenities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6PPC—water	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6PPC—neighbors (incl. ln house price)	–	–	–	–	Yes	Yes	Yes	Yes
FE	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr	5PPC/yr
$<X$ m flood safe 6PPC	<100 m	<100 m	<100 m	<100 m	<100 m	<100 m	<100 m	<100 m
No. obs.	41,756	42,455	42,455	42,398	38,858	38,858	38,858	38,858

Notes: Standard errors clustered at the 6PPC level in brackets. See Online Appendix C for a detailed description of all control variables observed at the 6PPC level that we include in our regressions. ln hh income stands for the natural logarithm of household income relative to the mean Dutch household income in each year. *Significant at 10%; **significant at 5%.

Columns (2)–(4) and (6)–(8) show no evidence of taste-based sorting based on the three proxies that we use for households' flood safety preferences. Of course this is no exclusive evidence that taste-based sorting is not an issue. In fact, one could even take our earlier results in Table 5(b) as suggestive of taste-based sorting. Disregarding the insignificant effects up to expected maximum flood water levels of 50 cm, they imply a MWTP to avoid flood risk that is *higher at lower* flood water levels. This is difficult to reconcile with homogenous tastes for flood safety. This interpretation is however based on a very rough estimate of the way the house price—flood risk gradient depends on the expected severity of the flood. Without information on the exact distribution of flood safety preferences over the Dutch population it is very difficult to provide conclusive evidence on the relevance of taste based sorting, and to infer whether we, if at all, over- or underestimate average AWTP to avoid flood risk.[37] In the presence of taste-based sorting, our estimate is an upper bound on the AWTP to avoid flood risk for those who chose to live in the flood risk area (they could have paid more to avoid the risk, but chose not to). And, at the same time, it is a lower bound on the AWTP to avoid flood risk for those who chose not to live at risk of flooding (they could have bought a somewhat cheaper home in a flood risk area, but chose not to).

5. Interpreting our Main Findings

In this last section, we interpret our main findings using the hedonic model outlined in Appendix A. In particular, we use our estimates to answer four different questions. If

37. This depends on the exact distribution of preferences over the population, as well as on the availability of houses at different levels of flood risk.

necessary, we always detail the additional assumptions required that allow us to shed light on them.

1. Do the Dutch have Full Confidence in their Publicly provided Flood Defenses?

Our baseline estimate of AWTP to avoid flood risk immediately implies that the Dutch do not feel completely safe behind their dikes, see equation (1). The average Dutch person does not fully trust the publicly built flood defenses to keep him/her safe from flooding ($\rho(\tau) > 0$), nor the government's ability to fully compensate the damage to their house if a flood were to happen ($b(s, \tau) < 1$).

Taking the point estimates of AWTP to avoid different extents of flood risk reported in Table 5(b) seriously, we can nuance this a bit further. Notably, when assuming that people's flood risk perception and (marginal) preferences for each and every housing attributes do not differ between flood prone areas facing different maximum flood water levels, our estimates directly reveal how much more damage people expect in places with higher expected flood water levels. The point estimates in column (1) would then for example imply that people expect three times as much uncompensated damage with water levels reaching up to 80 cm instead of only 20 cm. Or, five times as much uncompensated damage when the house would be flooded by more than 2 m instead of only 50 cm. Furthermore the insignificant point estimates for 6PPC areas with expected flood water levels below 50 cm suggest that people in these areas do expect that the government will be able to fully compensate the (limited) flood damage their houses will incur in case of a flood.[38]

2. What is the Average Flood Risk Perception in the Netherlands?

Generally, it is impossible to separate people's flood risk perception from the other factors influencing AWTP in (1). However, if one is willing to make the, likely invalid, yet not uncommon,[39] assumption that consumer preferences are homogenous and linear in each and every housing attribute, one can easily show that our estimated AWTP is a direct measure of people's *average expected future flood damage*—measured as a percentage of the value of the house in the absence of any flood risk:

$$\alpha \approx \frac{1}{K} \sum\nolimits_k \left[\underbrace{\rho^k(\tau)}_{\text{perceived flood risk}} \; \underbrace{[1 - b^k(\bar{s}, \tau)]}_{\text{perceived flood damage}} \right] \tag{3}$$

38. Note that an alternative explanation of the insignificance of the price discount in 6PPC areas that would receive 0–20 cm of water in case the Dutch defenses fail, is possible inaccuracy of Deltares' predictions of these water levels (see Section 3.3).

39. Other hedonic studies that aim to gauge the welfare effects of non-marginal changes in their housing attribute of interest also often make this assumption, although they typically need to assume that preferences are homogenous and linear in their housing attribute of interest only (see, e.g., Chay and Greenstone 2005).

Moreover, it directly identifies *the average perceived likelihood of an all-destructive flood*. To see this, simply set $b^k(\bar{s}, \tau)$ equal to 0 in (3). Our estimated AWTP basically puts a lower bound on people's perceived likelihood of any other, less damaging, flood. Importantly, the assumption that allows for this interpretation implies that people are risk-neutral. Assuming people to be risk averse instead, one can still establish from (1) that, given our estimate of α, the implied perceived likelihood of a flood decreases in its perceived destructiveness.[40]

Using (3), our estimated AWTP to avoid flood risk of 1% thus implies that people expect a flood to happen at least once every 100 years. This is much more frequent than the official protection levels at which the Dutch government claims to uphold the country's defenses. In the best protected places they should reduce the likelihood of a flood to happen to once every 10,000 years. Even in places with the highest acceptable flood risk, their defenses are allowed to fail only once every 500 years. This finding is very much in line with recent survey evidence. The self-reported likelihood of a flood in these surveys is typically even higher (e.g., 7%–19% chance in the next 10 years (TNS Nipo 2006), or larger than 20% chance in the next 50 years (Bockarjova et al. 2010)).

Furthermore, the differences in WTP to avoid different extents of flood risk reported in Table 5(b) can be interpreted as evidence that people's perceived flood risk is higher in 6PPC areas facing higher expected flood water levels. This also corresponds to recent survey evidence that finds that the share of respondents correctly stating that their house runs the risk of being flooded is higher in places facing higher maximum expected flood water levels (see Watermonitor 2009).

3. Willingness to Pay for Additional Private or Public Flood Insurance?

A very simple multi-period extension to our baseline model (see Section A.2 in Appendix A), shows that we can also use our estimates to calculate the implied yearly amount an average household living in a house at risk of flooding is willing to pay to be fully insured against flood risk (over and above the taxes already paid for public flood protection):[41]

$$P_{ins} = \alpha m \left[P(\mathbf{H}, s > 0) \right] r \tag{4}$$

where $m[P(\mathbf{H}, s > 0)]$ is the median price of a house at risk of flooding in the Netherlands and r is the interest paid on an interest only mortgage. P_{ins} can be directly compared to the €400 per year that the Dutch government currently spends on protecting each of the 2.8 million houses in the Netherlands facing flood risk. Also, we can relate it to the average €131 people currently pay per year for their private home insurance

40. It also most likely means that our estimate is an upper bound on people's perceived flood risk. Pinpointing exactly by how much is difficult however. The reason for this is that risk aversion is more complicated to unambiguously define since the utility function in our model has multiple elements, that is, all housing attributes (see, e.g., Stiglitz 1969; Kihlstrom and Mirman 1974, 1981).

41. Section A.2 in Appendix A details the additional assumptions required to arrive at equation (4).

that does not cover any flood-related damage (COELO, Woonlastenmonitor 2011). Assuming a 3% mortgage interest rate ($r = 0.03$),[42] and taking the median price of a house at risk of flooding in 2011 (€243,000), our estimated 1% AWTP to avoid flood risk corresponds to a yearly flood insurance premium of €73. Taking our Table 5(b) estimates seriously, we can further fine tune this premium depending on the extent of the flood risk faced. This gives a yearly insurance premium ranging from about €36 in places facing less than 50 cm of water, to a maximum €146 in places facing more than 2 m of water in case the Dutch flood defenses fail. This is between 9% and 36% more than the annual amount of public money spent per house at risk to protect the country from flooding, and between 30% and 110% more than the €131 average annual home insurance premium in the Netherlands.

4. *Housing Wealth Lost due to the Expected Future Rise in Sea Levels?*

Finally, we can use our estimates to provide a tentative estimate of the impact of the expected future rise in sea levels on housing wealth in the Netherlands. Based on predictions of, among others, the Royal Dutch Meteorological Institute (van den Hurk et al. 2006), we first obtain the number of the currently flood safe houses that a future rise in sea levels would put at risk of flooding in a best-, medium-, and worst-case scenario with sea levels rising by 24, 100, and 150 cm, respectively.[43] Under the strong assumption of an unchanging WTP to avoid flood risk,[44] and assuming that the Dutch flood defenses are upgraded to keep offering the same levels of protection as they do today, we can then easily get an estimate of the loss in housing value due to rising sea levels by multiplying the value of these houses by our estimated WTP to avoid flood risk, α. Interestingly this loss would be realized without a single drop of water coming over the dikes. It purely arises by increasing the number of houses at risk of flooding as well as increasing the expected damage to the houses currently already at risk of flooding.

A 24, 100, or 150 cm rise in sea levels will put an additional 275,450, 1,233,620, or 1,562,545 houses respectively at risk of being flooded. The median price of these, currently flood safe, houses was about €250,000 in 2011. As a result, our estimated WTP to avoid flood risk of 1%, implies a tentative total loss of housing wealth of €0.7, €3.1, €4 billion in the best-, median-, worst-case sea level rise scenario, respectively.

42. This is based on the typical after-tax interest rate on an interest only mortgage in our sample period.

43. Future climate change will also increase the risk of river floods due to more erratic rainfall patterns in the upstream catchment areas of the Rhine and Meuse rivers. However, contrary to rising sea levels, these river floods will, although increasing in frequency, not lead to many currently flood safe areas becoming flood prone. Also, the few that do are much harder to identify using our available data. For a rise in sea levels this can be readily inferred from elevation data.

44. An ideal measure of welfare change would also take into account how consumers and suppliers of housing respond to the change in flood risk induced by these rising sea levels (by, e.g., moving or changing the amount or quality of housing they supply). Most likely this will mitigate the welfare losses that we report here. Obtaining consistent estimates of each consumer's offer and each supplier's bid function faces empirical challenges that we cannot credibly address using our data (see, e.g., Brown and Rosen 1982; Bartik 1987; Epple 1987; Deacon et al. 1998; or for more recent contributions Ekeland et al. 2004; Heckman et al. 2010). It therefore lies beyond the scope of this paper.

Again, our point estimates of AWTP distinguished by expected flood water level (see Table 5(b)) can further nuance these numbers. We require two pieces of additional information to be able to do so. First, the number of houses currently facing no, or less than 50 cm of water in case of a flood that would start facing either 50–80 cm, or more than 80 cm, of water in each of the three sea-level rise scenarios. And, second, the number of houses currently facing 50–80 cm of water in case of a flood that would start facing more than 80 cm of water in each of these three scenarios. Using these numbers, and the significant point estimates in column (1) of Table 5(b), gives us a total loss of housing wealth of €1.1 billion, €4.9 billion, and €8.1 billion in case of a 24 cm, 1 m, 1.5 m sea level rise, respectively. Especially in the latter two scenarios these numbers are substantially higher compared to those based on our estimated AWTP that does not distinguish by expected flood water levels.

6. Conclusions

This paper takes advantage of a unique, extremely detailed dataset on flood risk and house prices in the Netherlands to provide evidence on the price and perception of rare natural disasters. Our dataset allows us to employ an empirical design that credibly identifies people's willingness to pay to avoid flood risk off exogenous variation in flood risk only. We find that house prices are on average 1% lower in places that are at risk of flooding. This flood risk discount is more pronounced in neighborhoods with higher predicted flood water levels.

Our findings imply that the Dutch do not feel fully protected by the country's world class flood defenses, nor do they believe that the government will live up to its obligation to fully compensate any flood related damage in case of a breach in these defenses. In fact, interpreted through the lens of a simple hedonic house price model, our estimates imply that the average Dutch citizen expects a flood to happen at least once every 100 years. This is much more frequent than the official protection levels at which the government claims to uphold the country's flood defenses.

Depending on the predicted flood water level in their neighborhood, people are willing to pay between €36 and €146 per year to be fully insured against any future flood risk. This is between 9% and 36% more than the €400 per year that the Dutch government spends on the flood protection of each house at risk of flooding. And, it is between 30% and 110% more than the €131 average annual home insurance premium in the Netherlands. These numbers put an interesting perspective on the ongoing debate whether or not the costs of the Dutch flood defenses should continue to be borne by all Dutch citizens, regardless of the actual flood risk they, and their property, face. The future costs of keeping the Netherlands flood safe will further increase as a result of rising sea levels and more erratic rainfall patterns in the catchment areas of the Rhine and Meuse rivers. At least partly funding these costs by a flood tax paid only in areas at risk of flooding, or by exploring the possibilities of opening a market for flood insurance, should, in our view, be seriously considered. Especially so, as it may, based on our results, meet less resistance than the government thinks from the people living in flood prone areas.

Appendix A: A Standard Hedonic Model Incorporating Flood Risk

In this appendix, we show how we incorporate flood risk into an otherwise standard hedonic model. We pay specific attention to the assumptions that allow us to identify the average willingness to pay (AWTP) to avoid flood risk, people's flood risk perception, and future loss in housing wealth due to rising sea levels.

We follow the hedonic approach pioneered by Rosen (1974) and Freeman (1974), and extend it to incorporate the uncertainty that comes with owning a house in a place facing the (rare) risk of a natural flood disaster (see also Brookshire et al. 1985).

Suppose, each house in the Netherlands is defined by a vector of n different attributes $\mathbf{H} = (h_1, h_2, \ldots, h_n)$. Some are directly related to the house itself, for example, m^2 of floor space, number of rooms, size of the garden, and so forth, and others to neighborhood characteristics, for example, quality of the nearby schools, type of neighbors, distance to parks, or other (dis)amenities. On top of this, each house is also characterized by the flood risk it faces, s, where s denotes the centimeters of water that would enter the house in case the country's flood defenses fail and a flood happens. They fail with probability $\rho(\tau) \in [0,1)$, that depends negatively on the share of total income, τ, that the government collects as taxes to uphold the country's flood defenses: $\partial\rho(\tau)/\partial\tau < 0$.

Flood risk effectively imposes uncertainty about people's utility derived from housing.[45] If a flood happens, a house located on unsafe ground ($s > 0$) is damaged. The extent of this damage depends positively on s.[46] Also, part of this damage may be refunded by the government financed out of the flood taxes it collects. After this possible compensation, only a share $b(s, \tau) \in [0,1]$ of all housing attributes survives, with: $\partial b(s, \tau)/\partial s < 0$ and $\partial b(s, \tau)/\partial\tau > 0$.[47] In case the house is located on safe ground it is not damaged even if a flood happens: $b(0, \tau) = 1$. Consistent with the situation in the Netherlands there is no possibility to take out private insurance that covers any potential future flood damages.

All of the house's attributes together determine its price:

$$P = P(\mathbf{H}, s). \tag{A.1}$$

The negative of the partial derivative of $P(\mathbf{H}, s)$ with respect to the amount of water entering the house in case of a flood, $-\partial P(\mathbf{H}, s)/\partial s$, then gives the implicit marginal price that people are willing to pay for an additional bit of flood safety.

45. As most hedonic house price models do, we view a house as a consumption good only. See Bayer et al. (2016) for a recent model that also considers houses as an investment good.

46. The relationship between expected damage and the amount of water flowing into the house is not perfect. Flood damage also depends crucially on the time that the water is present in the house. This depends, among others, on the drainage properties of the soil, the spatial extent of the flood, as well as the time it takes to fix the breach in the flood defenses.

47. It is straightforward to allow different housing attributes to be differently damaged at the same flood depth level, s. Doing so provides little additional insights, and, more importantly, it is impossible to take these insight to the data given the absence of information on individual housing attributes.

The hedonic price schedule (HPS) in (A.1) is determined by the (partial) equilibrium interactions between consumers and producers in a competitive housing market. Each consumer's expected utility is the sum of their utility in case of a flood and their utility when no flood happens, each weighted by their respective likelihood,

$$V^k = \rho^k(\tau)U(X, b^k(s,\tau)\mathbf{H}, \boldsymbol{\xi}^k) + (1 - \rho^k(\tau))U(X, \mathbf{H}, \boldsymbol{\xi}^k) \tag{A.2}$$

where $k \in \{1, \ldots, K\}$ with K the total number of consumers, and $\boldsymbol{\xi}^k$ captures each consumer's preference parameters that we assume not to differ in the flood and no-flood state of the world. Note that we allow each consumer to have his/her own belief regarding both the likelihood of a flood $\rho^k(\tau)$ as well as about the damage incurred to each housing attribute, $b^k(s, \tau)$.

In both the flood and no-flood state of the world, utility depends on the consumption of a vector of housing attributes, $\mathbf{H}$, as well as that of a numeraire good X with price normalized to 1. We assume that the utility derived from the other good, X, is the same in the flood or no-flood state of the world. This effectively means that this good does not incur any damages in case of a flood.[48] Moreover, it means that the utility derived from good X is additively separable from that derived from housing,

$$U(X, \mathbf{H}, \boldsymbol{\xi}^k) = U^X(X, \boldsymbol{\xi}^k) + U^H(\mathbf{H}, \boldsymbol{\xi}^k).$$

Finally, without any loss of generality, it holds that for each h_i: $\partial U^H(\mathbf{H}, \boldsymbol{\xi}^k)/\partial h_i > 0$. For housing attributes negatively affecting utility it means that h_i measures the absence of these attributes, for example, safety instead of crime levels, or air quality instead of pollution. Similarly, $\partial U^X(X, \boldsymbol{\xi}^k)/\partial X > 0$.

Consumers maximize their expected utility subject to their individual budget constraint, $Y^k = P(\mathbf{H}, s) + X + \tau Y^k$, where Y^k denotes consumer k's income, and each consumer pays a (nondistortionary) income tax, that is, a share τ of his/her income, to the government for upholding the country's flood defenses and/or for a national flood damage compensation fund.[49] Note that, as is the case in the Netherlands, all consumers pay this tax, regardless of whether they actually live in a flood prone area or not.[50]

The first order conditions (FOCs) corresponding to each consumer's expected utility maximization determine what levels of $\mathbf{H}$, X, and s, he/she chooses to consume.

48. This assumption is only made for easy of exposition, and could be relaxed. Doing so does not add any substantial new insights. Also, it would be straightforward to add a term to (A.2) that captures any non-damage related disutility from the mere inconvenience experiencing a flood, or allow consumers' preference parameters to be different in the flood and non-flood state of the world.

49. We take this income as exogenous. It would be possible to make this income endogenous depending on, for example, hours worked and wages. It could even be done in a way to allow a potential flood to affect firms' production (and thus wages paid). This would however unnecessarily complicate things as people often do not work and live in the same location, each with a different degree of flood risk.

50. There are differences in taxes paid between the 24 different so-called "Water boards" that are responsible for keeping up the flood defenses in their region, as well as safeguarding the quality and quantity of drinking water. However, each household within the same Water board pays the same tax, regardless of whether their house would actually flood in case the defenses fail or not. Our empirical design takes explicit care of these differences between Water boards.

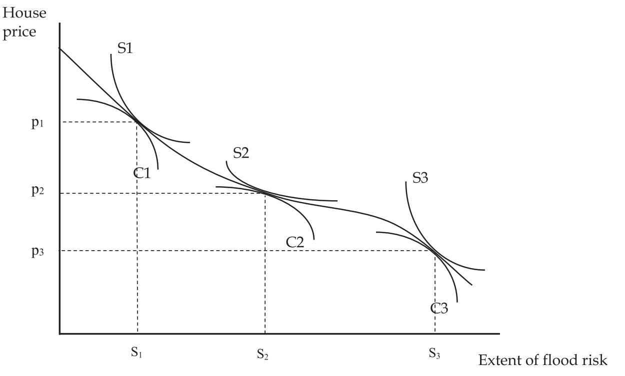

FIGURE A.1. Equilibrium hedonic price schedule in the hedonic market for flood risk. The figure depicts the bid functions for three different consumers (C1, C2, and C3), and the offer curves for three different suppliers (S1, S2, and S3).

At this preferred point of consumption, the FOCs provide an expression for each consumer's marginal willingness to pay for additional flood safety:

$$p_s^k = -\partial P\left(\mathbf{H}, s\right)/\partial s = -\rho^k(\tau)\frac{\partial b^k(s,\tau)/\partial s}{b^k(s,\tau)}\frac{\sum_{\mathrm{i}} U_{h_i}^H h_i}{U_X^X}, \tag{A.3}$$

where

$$U_X^X = \partial U^X(X, \boldsymbol{\xi}^k)/\partial X \text{ and } U_{h_i}^H = U_{h_i}^H = \partial U^H(b^k(s,\tau)\mathbf{H}, \xi^k)/\partial h_i.$$

Marginal willingness to pay for additional flood safety equals the expected marginal utility gain from moving to a house on safer ground in terms of the foregone marginal utility of X on which the consumer could have otherwise spent his/her (after tax) income. It differs between consumers as a result of differences in perceived flood risk, perceived flood damage in case of a flood, and preferences.

Equation (3) clearly shows that $p_s^k > 0$, unless people perceive the likelihood of a flood to be zero: $\rho^k(\tau) = 0$, or do not expect any difference in damage between their own house and an identical house with a lower degree of flood safety: $\partial b^k(s,\tau)/\partial s = 0$. In the Dutch context this means that they are either fully confident that the country's defenses will keep them safe, and/or they expect the government to be able to fully compensate them for any flood related damage in case the defenses do fail. Note that these beliefs need not be correct, p_s^k will be equal to zero as long as people *perceive* the likelihood of a flood, and/or its damage to be equal to zero.

Combining the individual specific budget constraint with (A.3), one can derive each consumer's bid function for s that reveals the maximum amount that he/she is willing to pay for different values of s while holding utility constant. Together with the supplier specific offer curves for s, that reveal the minimum amount of s that each supplier is willing to supply to the market while holding profits constant, they determine the equilibrium HPS for s. Figure A.1 illustrates this (see also Greenstone and Gallagher (2008) for a more in depth discussion).

The gradient of the HPS with respect to the extent of flood risk reflects the equilibrium differential that allocates consumers across the locations. It compensates consumers for living in areas with a higher risk of flooding, and, similarly, it compensates suppliers for the cost of supplying houses facing less flood risk. House prices in places facing a higher risk of flooding must be lower in order to attract potential buyers.

A.1. A Simple Multi-Period Extension

Assume that now each, infinitely lived, consumer maximizes expected utility over his/her entire lifetime:

$$W^k = \sum_{m=0}^{\infty} \left[\left(\delta^k\right)^m V^k_{t+m} \right], \tag{A.4}$$

where $0 < \delta^k < 1$ reflects the rate at with each consumer discounts utility in future periods, and V_t^k specified as in (A.2) with a subscript t added to X only.[51] At the start of his/her lifetime, each consumer buys one house that he/she will occupy for the rest of his/her lifetime, paying $rP(\mathbf{H}, s)$ as mortgage payment in each period, where $0 < r < 1$.[52] The rest of his/her after tax income, $(1-\tau)Y_t$, is spent on the outside good X so that the budget constraint in each period looks like: $(1-\tau)Y_t = rP(\mathbf{H}, s) + P_t^k X_t$. For simplicity we further normalize the price of the outside good to 1 in each period and assume that income is the same in each period.[53] It is straightforward to show that the FOCs of the consumer's lifetime expected utility maximization problem subject to his/her budget constraint in each period now imply the following MWTP for an additional bit of flood safety:

$$p_s^k = -\partial P(H, s)/\partial s = -\rho^k(\tau) \frac{\partial b^k(s,\tau)/\partial s}{b^k(s,\tau)} \frac{\sum_{\mathrm{i}} U^H_{h_i} h_i}{U^X_X} \frac{1}{r} \tag{A.5}$$

51. This means that we assume that people's flood perception, the damage to each and every housing attribute that they expect in case of a flood, as well as their preferences do not change over time. Also, no subscript t is added to $\mathbf{H}$ as people buy their house at the start of their lifetime and live there throughout their entire life.

52. Note that most people in the Netherland actually took out such an interest only mortgage over our sample period. Up until 2013, the tax system in the Netherlands encouraged people to take out such a mortgage since all mortgage interest payments were fully tax deductible.

53. We could relax these two assumptions. They do not affect our conclusion regarding MWTP for additional flood safety. It would only mean that this MWTP depends additionally on people's time preference parameter δ^k, and on their expectations of both their income and of the price of the outside good in each future period. Making these simplifying assumptions allows us to write MWTP in a way that is almost (up to $1/r$) equivalent to that in our baseline static hedonic model, see (A.3).

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Supplementary Data

Supplementary data are available at *JEEA* online.