River Flooding and Housing Values: An Economic Assessment of Environmental Risk*

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Abstract

Climate change and river management practices have resulted in significant changes in the spatial distribution of the risk of river flooding. Over the last few decades, the risk of flooding has on average increased for locations close to the river bed. Assessing the incidence of spatial risk and the implicit price of the risk of river flooding is the subject of a series of hedonic pricing studies, predominantly pertaining to locations in the US. Using value estimates and their associated standard errors derived from these hedonic pricing studies, we perform a meta-analysis. Specifically, we assess whether the variation in the percentage change in the price of a house located in a floodplain, as compared to houses located outside the floodplain, is merely due to sampling variation or whether the variation can be associated with structural differences. We showed that the choice of explanatory variables of hedonic price functions affects the variability between estimates, as well as the type of data. The level of income has been identified as a means to protect from risk vulnerability, and it has been observed that the implicit price of flood decreased over time. Factors related to the exploitation of spatial characteristics of the data such as the use of a GIS did also play a role. Finally, it appeared that specific attention has to be paid to the perceived level of risk; elements affecting the perception of individuals on the effective risk of flooding and allowing them to update their perception of the level of risk explained variability between estimates.

Key words: valuation, risk, river flooding, meta-analysis, hedonic pricing

JEL Codes: D81, H54, Q51, Q54

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1. Introduction

The occurrence of floods, windstorms and heat waves receives increasing media coverage. This is partly due to improved technology in communication and broadcasting infrastructure, but it is also a result of a higher incidence of natural disasters. Over the last few years many European countries, including Italy, France, Austria, Great Britain, Germany and Greece, incurred sizeable human and material losses due to river floods. The increased incidence of river flooding has both natural and anthropogenic causes.

Climate change, which is simultaneously caused by changing natural circumstances as well as human behavior results, brings about an increase in the frequency of river flooding as well as its magnitude in most regions of the world. For instance, a 0.5 to 1% increase of land-surface precipitation per decade has been observed in much of the mid and high latitudes of the Northern Hemisphere's Research has also shown that the frequency of heavy precipitation has likely increased by 2 to 4% over the last 50 years, and a 0.6°C increase in global temperature over the last century has impacted sea levels with concurrent impacts on the transport speed and capacity of rivers (IPCC 2001).

Anthropogenic impacts on river flooding are even more clearly visible in changed river management practices. Construction in floodplains, channel straightening, building of dikes, and construction activity generating impermeable surfaces such as transport infrastructure and residential areas are examples of urbanization that increases the risk of river floods in small catchment areas and small river networks. Land use conversion is also a factor changing the spatial distribution of risk. Particularly in developing countries deforestation for agricultural purpose causes intensified sediment transport rates of rivers and of deposition downstream (Kron 2003).

A spatial economic assessment of environmental risk is important in view of decision-making on public and private investments in protective infrastructure reducing the impact of environmental disasters. An appropriate assessment also assists in the design and provision of price-efficient insurance policies against environmental risk.

Rational investment behavior of economic actors is guided by a simple cost-benefit rule. For instance, Dantzig (1956, p279) already notes that the optimal height of a sea dike is determined by "taking account of the cost of dike-building, of the material losses when a dike-break occurs, and of the frequency distribution of different sea levels." The cost of protective infrastructure comprises outlay for the construction of a dike and the subsequent nuisance it generates, with benefits accruing in terms of avoided human losses, material losses and reconstruction costs, crops losses, and breaks in economic activity.

Reliable information regarding actors' willingness to pay for a reduced exposure to the risk of river flooding is needed for a proper cost-benefit analysis of investments in protective infrastructure as well as for efficient insurance pricing. The unpredictability of the risk and damage magnitude of river flooding as well as problems of asymmetric information and adverse selection make price-setting behavior difficult (Akerlof 1970).

Two types of private insurance can be distinguished, the so-called optional system and the package system (Paklina 2003). The first variant clearly suffers from adverse selection, because it extends the standard policy to flood damage coverage in return for additional premium. In the bundle system, flood damage coverage is available along with other risks, such as fire, earthquakes and hurricanes.

The legal system in the US has been more conducive to opening the possibility of private insurance. In 1968, Congress instigated the National Insurance Act which called for the implementation of the National Flood Insurance Plan (NFIP, see Browne and Hoyt 2000; Harrison, Smersh et al. 2001; Troy and Romm 2004). The NFIP stipulates the availability of flood insurance when a community agrees to adopt and enforce flood mitigation and land use regulations. In the "emergency phase" flood hazard maps are provided and residents of zones at risk are allowed to purchase a limited amount of insurance at subsidized rates. In order to enter the "regular phase," communities have to adopt additional flood mitigation and land use measures in return for extended insurance coverage. Because the NFIP suffered from a very low participation rate, Congress passed the Flood Disaster Protection Act (FDPA) in 1973. Under FDPA regulations participation is mandatory. Mortgage provision for property located in a flood zone is conditional upon obtaining catastrophe insurance which effectively qualifies as a guarantee securing the loan.

Effectively, in the context of an assessment of the risk of river flooding we are searching for an estimate of implicit price for self-protection (the price of safety), or the capitalization of insurance premiums in the price of the house, and of damage not covered by insurance, such as the nuisance related to the (partial) destruction of the house and belongings, and to the delays of reconstruction. An inventory of flooding risk valuation studies available in the empirical literature shows willingness to pay (WTP) estimates ranging from –0.229 to +0.575% of the average price of houses for a probability of risk exposure of 0.01 per year. The variation in estimates may merely represent sampling or estimation variance, but it may also be caused by systematic variation in the unobserved population or sample values of the willingness to pay for reduced risk of river flooding exposure. Meta-analysis, which comprises an array of statistical techniques to analyze previously published empirical estimates, can be used to determine the extent of random versus systematic variation. It is a well known and popular tool in the context of non-market valuation of air pollution, recreational fishing, health risks, endangered species, wetlands, and pesticide risk exposure (Woodward and Wui 2001; Travisi, Nijkamp et al. 2004).

The remainder of this paper is organized as follows. The next section deals with the use of valuation techniques in the context of river flooding risk assessment. Section 3 briefly discusses the sampling of studies, and provides the main characteristics of the estimated WTP for reduced risk exposure. We also determine whether the sample drawn from the literature is distorted because of publication bias. In Section 4 we provide an overview of factors that are potentially relevant in explaining structural variation of risk valuations, and we present the estimation results for the meta-regression analysis. Section 5 concludes.

2. Valuation, externalities and perception bias

Stated as well as revealed preference methods are being used to assess flood risks, and both types of methods have their own advantages and disadvantages (see Freeman (2003), for an overview). Stated preference methods are based on interviews or surveys explicitly asking individuals about their willingness to pay for reduced flood risk exposure, using contingent valuation or choice experiments such as conjoint analysis or contingent ranking. Advantages of stated preference methods include the possibility to give respondents accurate information about the envisaged risk, the consideration of both actual and hypothetical scenarios, and the opportunity to assess use as well as non-use values. Arguably, the major disadvantage of stated preference methods is that it remains unclear whether the actual behavior of respondents corresponds to their statements. List and Gallet (2001) show that, especially in risk assessment valuations, the impact of the so-called hypothetical bias is most likely strong.

The revealed preference method is concerned with actual consumer behavior in markets. The restriction to actual behavior obviously restricts the method's ability to assess WTP values in different (real-world) situations, and one cannot readily control the information shaping the risk perception of individuals. De Blaeij et al. (2003), and Travisi et al. (2005) are examples of studies dealing with the valuation of risk. They both show that revealed preference techniques lead to significantly lower WTP values than stated preference techniques.

Most of the studies assessing the value of flood risk exposure use the revealed preference approach. The assumption underlying revealed preference studies in the presence of an environmental risk is that an exogenously determined (set of) risk(s) is considered when choosing the location of a house. Housing prices then reveal individual preferences regarding the acceptance of risk, assuming that appropriate controls for differences in the property and the location are accounted for. A straightforward technique to assess such differences is to look at the average difference between prices of houses located inside and outside a zone at risk, and to compute a significance test for the equality of these differences. This difference in means estimator has been used in, for instance, Zimmerman (1979) and Shrubsole et al. (1997).

A more elaborated technique derives from Rosen's (1974) seminal paper, in which a housing unit is considered as a differentiated market good representing a bundle of quantitative and qualitative characteristics. Implicit shadow prices can be determined as the partial first derivative of an econometric model that relates the observed selling price of a house (p) to a set of characteristics proper to the house, and characteristics of the neighborhood or location of the house. It is important to note that p is the equilibrium price on the housing market, and variables describing the process of equilibrium price formation should not be part of the hedonic price function[1]. A subset of the neighborhood or location characteristics can be concerned with environmental aspects, such as the risk of natural hazards, and air quality. Location choices hence include the choice of consuming a particular *level of risk*.

In the hedonic valuation of spatially differentiated environmental risk, two potential problems need careful consideration. One is the potential bias in individual perceptions of the level of risk, especially because in hedonic pricing models, as compared to stated preference studies, no additional information or explanation is provided to consumers. Another problem is caused by the coincidence of water-related amenities with water-related risks.

Perception bias amounts to the divergence between the objective probability of a given risk and an individual's perception of the risk. A proper appraisal of objective hazards, for instance determined on the basis of recurrent patterns, can interfere with individual personal characteristics and subsequently give rise to biases in the perception of hazards. Specifically, an individual may be completely blind to a risk, in which case revealed preference techniques are of little relevance. Alternatively, individuals may perceive reality through a distorting mirror, in which case revealed WTP values are over- or under-estimated (Viscusi 1991). Both expected utility theory and prospect theory are in line with the observation of individuals over-estimating low probability events (Kahneman and Tversky 1979; Viscusi 1991), especially if fears are present, and under-estimating risks over which individuals may have active control (Viscusi 1991).

A way to identify differences between objective and subjective probabilities of risk is to obtain estimates before and after an event. New information that can potentially affect subjective probabilities and make them compliant to the objective vulnerability can take the form of: the occurrence of the event at risk and the individuals' experience with such an event, a concurrent change in insurance premiums, a change in disclosure rules concerning a specific risk, and increased visibility of the risk, due to for instance an increase in media coverage. An illustration of the overestimation of low probability events is provided in Beron et al. (1997). They show that the devaluation of housing prices due to the location in a zone at risk drops from 4% before the Loma Prieta earthquake in 1989, to 3.4% after the quake.

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[1] Some studies include the number of days on the market as a conditioning variable in the hedonic price function, although this does not seem to be appropriate. Such a variable reflects either the accuracy of the

Scarcity of information is also relevant with respect to the second complication, the confounding of positive and negative externalities related to proximity to the river. The risk of flooding can be caused by exceptional rainfall, but it is likely to be independent of rainfall in regions endowed with rivers, canals, or lake watersheds, located nearby the coast or at a low elevation levels. In those cases the presence of water is associated with positive (e.g., visual amenities, water sports facilities, and open space) as well as negative spatial externalities (hazard of river flooding). As a result, a simple dummy variable signaling location within or outside a floodplain may effectively underestimate the value of the risk of river flooding, because positive and negative water-related externalities are not separately identified and may hence partly cancel in the capitalization of externalities in housing prices. Advanced computational techniques and the use of geographic information systems have improved the extent to which researchers can account for the spatial organization of the data in terms of distance to water and elevation. It is expected that amenities and risk do not exactly coincide. For instance, houses with a direct view on a river may have no canceling valuations for flood risks and amenities, whereas for houses with a view but at a lower elevation the valuations may cancel. This problem is addressed in the meta-analysis by controlling for the inclusion of distance and elevation related variables in the primary studies.

3. The determinants of the assessed value of flooding risk

It has to be noted that primary studies included in the meta-analysis all present estimates for the United States, where flood insurance is available.

This section gives a short review on the National Flood Insurance Program; next, the selection criteria for primary studies are presented. Finally, a meta-regression analysis is used to identify the determinants of variation in flood risk assessment across primary studies.

3.1. The selection of primary studies

The collection of studies to include in the database takes place under two conflicting viewpoints. On the one hand, a high number of observations allows statistical inference to

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asking price versus the actual market price, or it reveals an unexplained selling difficulty specific to a house.

be of good quality. On the other hand, the desire to save degrees of freedom motivates the ambition of getting a homogeneous data set, and of limiting the number of control variables necessary to describe the data (for instance, studies built on a unique design, and presenting a very small number of estimates).

In order to be selected, a study needed to meet the following requirements:

(i) the assessed price of flood risk is the result of the application of a RP technique (difference in means estimator or hedonic price model), and can be presented, even indirectly, as a percentage of the average price of the house

(ii) the risk of flooding is captured by a dummy, and the dummy refers to a certain expected occurrence of flooding; most of the studies concern the implicit price of the location of a house within a 100-year floodplain contour, i.e. on average a minimum chance of being flooded of 0.01 per year.

(iii) the implicit price of a given risk of flooding is not the replication of a previously obtained result

As a matter of illustration, requirement (i) impeded the inclusion of a study giving a $ change in price due to the location in a floodplain, not related to the average price of houses (Thompson and Stoenever 1983; Holway and Burby 1990). Requirement (ii) was somehow more restrictive and led to the exclusion of studies using elevation and flood depth as control variables (Barnard 1978; Tobin and Montz 1994; Kriesel and Friedman 2002; Zhai and Fukuzono 2003). In spite of these restrictions, 19 studies could be collected in a first stage, gathering 89 estimates.

Among them, 2 studies only, each reporting a single estimate, concerned difference in means estimators (Zimmerman 1979; Shrubsole, Green et al. 1997). The inclusion of these two point estimates would oblige to add two dummies, one indicating the use of a difference in means estimator, the other the location in Canada. The exclusion of these two points is justified by the fact that additional information brought by the inclusion of the corresponding studies is not supposed to offset the related additional heterogeneity in the database. Another study was excluded on the basis that it only concerned land prices (Shabman and Damianos 1976); the inclusion of a dummy for this single estimate was for the same reason not appealing.

The final database is made up of 16 studies and 86 points. Please refer to Appendix 1 for a presentation of the most striking features of these studies.

Selected studies defined the risk of flooding as the presence in an X-year floodplain, which means that the probability of being flooded is 1/X in a year. Donnelly (1989) defines it in a slightly different way, as the risk variable is the product between the usual flood dummy and the property's tax liability. The coefficient associated to this risk variable then gives the difference in the selling price due to the location inside or outside the floodplain, per dollar of property tax liability. The reported change in price is then computed for the average property tax.

The included studies have as dependent variable the actual selling price of the house, except in one study presenting 13 estimates for which prices were appraised (US Army Corps of Engineers 1998).

In accordance to the discussion given in section 2., a recurrent approach to account for subjectivity in probability assessment is to make use of estimations before and after an event supposed to modify individual perception. The occurrence of a disaster, by enhancing individual experience, is the first means used for this purpose (MacDonald, Murdoch et al. 1987; Skantz and Strickland 1987; MacDonald, White et al. 1990; US Army Corps of Engineers 1998; Fridgen and Shultz 1999; Bin and Polasky 2003; Hallstrom and Smith 2004).

But changes in insurance design are also considered, such as the National Flood Insurance Reform Act of 1994 (Harrison, Smersh et al. 2001), or the California Natural Hazard Disclosure Law (Troy and Romm 2004).

The effect size under scrutiny is the relative implicit price of the risk of flooding, also interpreted as the relative change in the price of a house located in a specific zone at risk, due to this specific risk.

The expression of the effect size *theta* is itself dependent on the functional form of the primary hedonic price function, as well as its corresponding standard error. Most of the studies make use of the semilog form, which means that the estimated coefficient is equal to *theta*. However, other functional forms have been used in some cases, and the estimated coefficient had to be transformed to make it equal to *theta*. Table 1 presents the different expressions of both the effect size and its standard error.

Functional form of the primary hedonic price function	Dependent variable of the primary hedonic price function	Effect size	Standard error of the effect size
Linear	P	$\frac{\hat{\beta}}{\overline{P}}$	$\frac{se(\hat{\beta})}{\overline{P}}$
Semilog	ln P	$\hat{\beta}$	$se(\hat{\beta})$
Box Cox transformation	$\frac{P^{\lambda}-1}{\lambda}$ if $\lambda \neq 0$	$\frac{(\overline{P}^{\hat{\lambda}}+\hat{\lambda}\hat{\beta})^{1/\hat{\lambda}}}{\overline{P}}-1$	$\left(\frac{\overline{P}^{\hat{\lambda}}+\hat{\lambda}\hat{\beta})^{1/\hat{\lambda}}}{\overline{P}}-1\right)\frac{.se(\hat{\beta})}{\hat{\beta}}$

$\hat{\beta}$ estimated coefficient

$\overline{\mathrm{P}}$ sample mean of the selling price

Table 1 Expression of effect sizes and standard errors

Theta is to be understood as the relative change in the price of a house located in a specific zone at risk, given a risk level (to be specified as a control variable). Complementary, *thetalevel* is the relative price of risk per level of risk, and is simply computed as:

$$thetalevel = \frac{theta}{\text{probability of risk} * 100} \tag{1}$$

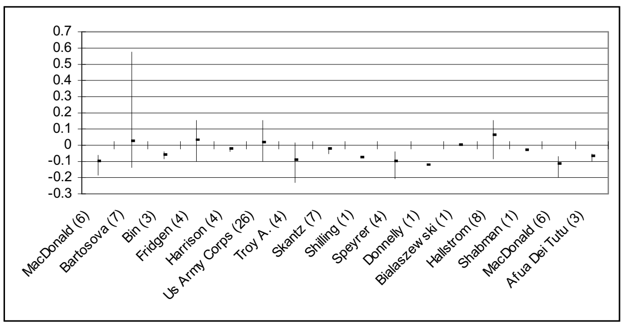
For a level of risk equal to the standard 100-year floodplain, *theta* and *thetalevel* are identical. Standard errors of *thetalevel* are obtained by replacing *theta* by its corresponding standard error in equation (3).

In the case an effect size is made up two elements, for instance $\hat{\beta}=\hat{\beta}_1+\hat{\beta}_2$, its estimated variance is computed as follows:

$$est.se_{\hat{\beta}} = \sqrt{var(\hat{\beta}_1)+var(\hat{\beta}_2)+2\,cov(\hat{\beta}_1,\hat{\beta}_2)} \tag{2}$$

The covariance of the estimates is not provided in the studies and is approximated by $0.6*se(\beta_1)*se(\beta_2)$.

Among the 86 point estimates, the relative change in house price due to the risk of flooding typically ranks from 0 to -10% of the average selling price (Figure1). However, because of the inclusion or not of new information likely to modify subjective probability of risk, and to the variability in other factors included in the primary hedonic price models, average values and range of variability are rather different between studies. Indeed, *theta* fluctuates from -0.268 to 0.156, with an average value of -0.031 (see Figure 2). This means that the selling price of a house is on average 3.1% lower than the one of a similar house located outside a zone at risk, without controlling for the exact level of risk. *Thetalevel* fluctuates from -0.229 to 0.575, with an average value of -0.021. The selling price of a house located in the standard 100-year floodplain is on average 2.1% lower than the one of a similar house located outside the zone at risk. The presence of outliers in Figure 1 is appealing as it brings variation in the data set, valuable for the estimation process.



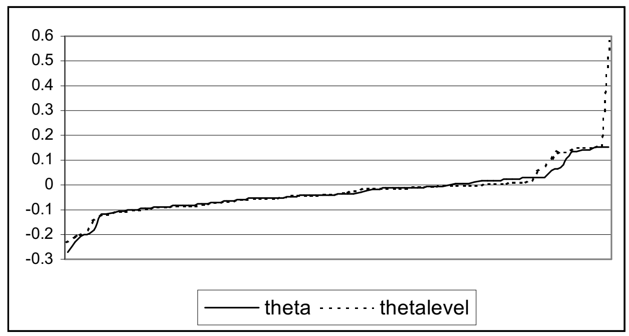


Figure 1 Minimum, maximum and average values of the effect size *thetalevel* per study (identified by the name of the first author; number of estimates per study in parenthesis) (left); Effect size ranked by increasing values (right)

3.2. Estimation process and results

The objective of an exploratory meta-regression is to determine the elements that have an influence on the level of the estimated relative change in selling price due to the risk of flooding reported in the original studies. Button and Jongma (1995) advise to include the following moderator variables:

- the characteristics of the research methods used in each study and the data used
- the period covered by each study to allow for any underlying dynamic effect
- the location of the study
- the variables defining the specific causes of the problem
- the features of those affected by the problem

This framework is slightly adapted, and the meta-regression has the following form.

$$Y=Y(\mathbf{D}, \mathbf{L}, \mathbf{R}, \mathbf{V}) \qquad (3)$$

with Y the relative change in selling price due to the risk of flooding, and **D**, **L**, **R** and **V** vectors of explanatory variables (see Appendix 2 for the complete list of variables).

***D**: vector of variables describing the research design of the original HPM*; this vector corresponds to the first two categories of moderator variables mentioned earlier

***L**: vector of variables catching some locational characteristics;* this corresponds to the third item of the framework.

***R**: vector of variables describing the risk of flooding*

***V**: vector of indicative variables describing the variables included in the original HPM*

These last two vectors correspond to the last two items of the original framework.

The complete data set is made up of 86 observations, 50 variables (among which 44 dummy variables), 2 identification variables (a study and an estimate id number), 2 effect sizes variables (*theta* and *thetalevel*) and 2 standard errors of effect sizes (*thetase* and *thetalevelse*).

Multi-collinearity is obviously a problem in this model. It is likely that some dummy variables catch the same underlying effect, because of the clustered design of the data set. This is the why reason we proceed to a selection among them.

A preliminary choice is made on the basis of the relevance of the inclusion of these variables, in order to retain 24 indicator variables. We start dropping variables present in a single study, such as the use of White Standard errors or weighted least squares, or the fact that estimation is done with a house price above or below the average sample price. Location dummies are also eliminated, because it happens that 70 observations correspond to samples drawn in the Southeast region; this information is expected not to bring supplementary information. Furthermore, dummies related to the presence in an X-year flood plain, with the exception of the 100-year floodplain, are dropped. Lastly, the dummies indicating the use of cross-section data, time series or panel data are removed, because the use of a single dummy indicating the use of time series or panel data (in opposition to cross section data) seems more informative.

The 24 remaining dummy variables are not subject to perfect collinearity. Regarding multi-collinearity, we investigate the probability of getting a certain category of variables in the original study, conditional on the inclusion of another variable. Considering two dummies, X_i and X_j, we are interested in the probability of getting $X_i=1$ given $X_j=1$, which can be written as:

$$Prob(X_i = 1 | X_j = 1) = \frac{Prob(X_i = 1 \cap X_j = 1)}{Prob(X_j = 1)} \quad (4)$$

With $Prob(X_i = 1) = Card(X_i = 1)/N$, where N is the number of estimates and Card(X_i=1) is the number of elements equal to 1 in the X_i vector. We can write:

$$Prob(X_i | X_j) = \frac{Prob(X_i = X_j = 1)}{Prob(X_j)} = \frac{Card(X_i * X_j = 1)}{Card(X_i = 1)} \quad (5)$$

And it is not difficult to show that this can easily be computed as:

$$Prob(X_i | X_j) = \frac{\sum X_i \cdot X_j}{\sum X_j} \quad (6)$$

Computation of conditional probabilities gives a 24x24 table, presented in Appendix 3. Variables of little interest are the one systematically present or absent when another variable is present, because they are supposed not to bring so much new information. The following variables have been excluded: level of pollution, tax level and insurance premium as conditioning variables in the primary study, assessed selling price as dependent variable, delay on the market before being sold, and very high probability of flood.

Concerning the other types of variables, not all of them are used. The number of degrees of freedom is dropped because it can inform on the quality of data, which is to be enclosed in the model by the standard error of the effect size. Time span is also dropped because it is an indication on the type of data, which is already latent in the dummy time series or panel data. Table 2 reviews the covariates to be used during the estimation stage.

	dummy	mean	se	min	max
semilog dummy is 1 if semilog specification in the primary study, 0 if linear or Box Cox	d	0.37	0.49	0	1
Box Cox dummy is 1 if Box Cox specification in the primary study, 0 if linear or semilog	d	0.19	0.39	0	1
geocoded dummy is 1 if data is geocoded in the primary study, 0 otherwise	d	0.29	0.46	0	1
time series / panel data dummy is 1 if data in the primary study is times series or panel data, 0 if cross section	d	0.38	0.49	0	1
comfort dummy is 1 if a comfort variable was used as a primary covariate, 0 otherwise	d	0.60	0.49	0	1

neighborhood dummy is 1 if a neighborhood variable was used as a primary covariate, 0 otherwise	d	0.36	0.48	0	1
quality dummy is 1 if a quality variable was used as a primary covariate, 0 otherwise	d	0.74	0.44	0	1
accessibility / distance dummy is 1 if an accessibility or distance to amenity variable was used as a primary covariate, 0 otherwise	d	0.40	0.49	0	1
finance dummy is 1 if a variable indicating a conventional loan was used as a primary covariate	d	0.14	0.35	0	1
exact level of flood risk probability of occurrence per year		0.02	0.04	0.002	0.2
low level of risk dummy is 1 if the probability of risk is lower than 0.01 per year	d	0.09	0.29	0	1
100-year floodplain dummy is 1 if the probability of risk is equal to 0.01 per year, 0 if it is lower or higher than 0.01	d	0.70	0.46	0	1
after change in info dummy is 1 if primary estimation occurs after the occurrence of a disaster or after a change in insurance patterns, 0 otherwise	d	0.36	0.48	0	1
income*1000 household median income in the corresponding county, in constant 2003-dollars		35.09	6.77	23.97	53.27
median sample year median year of the time span of the primary study		12.23	6.5	0	21
publication year		9.52	5.69	0	17

Table 2 Set of explanatory variables in meta-regression

Estimation is to be done alternatively with the dependent variable *theta* and *thetalevel*, in order to check to what extent a change in the definition of the effect size can affect the results. The aim is to carry out an exploratory meta-analysis that can explain variation in effect sizes.

A first point of concern is the risk of publication bias (Sutton, Sheldon et al. 2000). Studies reporting significant and positive results might be more likely to be published than insignificant or negative results. Figures 1 did illustrate the high variability in the original estimates. Publication bias is further investigated by considering the plot of effects size versus their inverse standard error, namely the funnel plot, and by carrying out two statistical tests.

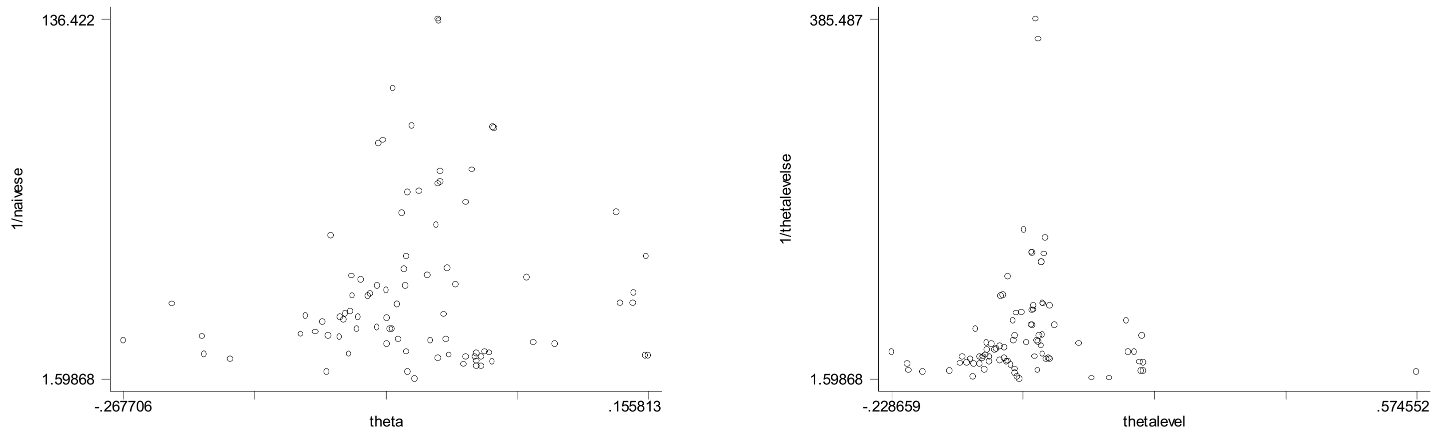


Figure 2 Funnel plots of the effect sizes

Begg's test (adjusted rank correlation test): investigates the relation between effect estimates and their variances.

z=0.59 (p=0.56) for *theta*, and z=-0.43 (p=0.67) for *thetalevel*

Egger's test (regression asymmetry test): investigates the asymmetry of the funnel plot by determining whether the intercept deviates significantly from zero in a regression of the standardized effect estimates against their variance.

t=-1.19 (p=0.237) for *theta*, and t=-1.58 (p=0.119) for *thetalevel*

The visual interpretation of the funnel plot (reasonably symmetric) and these two statistical tests show no evidence of publication bias.

A second point of concern is the source of variation in the effect sizes. Homogeneity in the data set means that variation in the effect size is random, and exclusively caused by sampling. This means that there are no systematic differences between studies. On the contrary, heterogeneity means that variation in the effect size is due both to sampling and real differences between studies. This is investigated by testing the null hypothesis: $\theta = \theta_1 = \theta_2 = ... = \theta_k$ (all studies are estimating the same underlying effect size (Sutton, Sheldon et al. 2000)).

With k the number of studies being combined, T_i the effect size estimate of the i^{th} estimate and w_i the reciprocal of the variance attached to the i^{th} estimate, the Q-test is computed from:

$$Q = \sum_{i=1}^{k} w_i (T_i - \overline{T}.)^2 \text{ with } \overline{T}. = \frac{\sum_i w_i T_i}{\sum_i w_i} \tag{7}$$

The Q-test gives values of 519 for *theta* and 522 for *thetalevel*. It appears that data is heterogeneous; real differences exist between studies.

Given that data is heterogeneous and that no publication bias is identified, the so-called mixed-effect model is estimated by the maximum restricted likelihood (Thompson and Sharp 1999). This model accounts for residual heterogeneity that cannot be explained by the covariates, and can be expressed by the following:

$$\begin{aligned} T_i &= \beta_0 + \beta_1 X_{i1} + \ldots + \beta_p X_{ip} + u_i + e_i \\ var(T_i) &= \tau^2 + v_i \end{aligned} \tag{8}$$

With T_i the effect size estimate, that is to say *theta* or *thetalevel*.

This model includes a two components error term: a random effect component accounting for the variation in effect size estimate not predicted by the model (u_i), and a component accounting for the within study variation (e_i).

Besides the use of a different dependent variable, estimation strategies differ by the choice of using either as a trend variable the variable *year of publication* or *median sample year*, and by the choice of the risk variable (continuous, or dummies). All possible full specification models are estimated as mixed-effects models. Then, reduced specification is obtained by deleting one by one variables associated with non-significant parameter estimates (p=0.1), with the restriction that coefficients corresponding to the level of income and to the level of risk have to be significant.

It is important to note that signs and range of estimates are consistent across strategies. Table 3 reports both full and reduced specifications of the model to be discussed in the next section.

4. Discussion

The prediction capacity of the model seems to be of good quality. Indeed, giving an average value to all covariates provides an estimated treatment effect of -0.0303, which is very close to the actual average value of the effect size (-0.0305).

Dependent variable: theta Estimated between variance study:0.000077		
Probability of risk	-0.63767	-0.62945
	(0.27936)**	(0.27241)**
Level of income	-0.00031	0.00137
	(0.00109)	(0.00058)**
Boc Cox transformation	-0.00217	
	(0.01232)	
Semilog transformation	0.00038	
	(0.00961)	
Use of geocoded data	-0.10701	-0.10557
	(0.01247)***	(0.01076)***
Time series or panel data	0.03847	0.03653
	(0.01115)***	(0.00743)***
Comfort	0.04837	0.03256
	(0.02228)**	(0.01318)**
Neighbourhood	0.03014	
	(0.01599)*	
Quality	-0.00074	
	(0.02437)	
Accessibility or distance	-0.02291	-0.02722
	(0.01417)	(0.00980)***
Finance	0.11102	0.09204
	(0.01693)***	(0.01116)***
After a change in information	-0.01970	-0.02294
	(0.00895)**	(0.00825)***
Year of publication	0.01286	0.01159
	(0.00169)***	(0.00103)***
Constant	-0.15243	-0.17213
	(0.02740)***	(0.02133)***

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3 Estimation results

It is commonly stated that in modern societies, improvements in safety and health levels go together with an increased concern about risk (Kunreuther 1996), so that an increase in quality of life would make people more risk averse. But the present estimates contradict this argument twice. First, because wealthy house buyers tend to have a lower willingness to pay to reduce the risk of flood, it seems that the level of income protects from risk vulnerability. Accounting for a median household income of 35000 USD (2003), the estimated treatment effect is positively affected by more than 0.05. Then, it appears that, as time goes by, the implicit price of flood risk decreases.

Concerning the significance of parameters associated to the presence of certain covariates in the primary studies, the signs and ranges are not relevant from an economic point of view. However, it is important to note that the omission of these covariates in primary studies could lead to a bias in estimates. Keeping other things equal, the presence of variables describing comfort characteristics of a given house (presence of a fireplace, central heating) in the hedonic price regression lower the estimated implicit price of flood risk. The relative change in price of a house due to the risk of flooding is affected in this case by 0.033. Thus, the omission of certain variables in the primary study may lead to an underestimation or overestimation of the implicit price of flood risk.

The type of data (cross-section or not) also seems to influence the effect size estimates, though again the direction of this variation has no theoretical support. It is interesting to point at the coefficient affected to the dummy indicating the use of a GIS in the primary study: it appeared to be systematically negative and relatively high across all specifications. It can be that giving a spatial dimension to data helps to reveal in a more systematic way the devaluation of houses at risk, and that estimates are merely of better quality.

A final point to be discussed concerns the awareness of house buyers. It appears very clearly that when a house buyer has the opportunity to update his knowledge on flood risk, the implicit price of risk gets higher (-0.023). This better knowledge is the result of a recent experience with flood or of better provision of information from insurance companies. Hence, improving information to house buyers can help them assessing more accurately the risks. It can also be that they over-react. This has two consequences. First, it questions the methods risk communication. Providing information on very small probabilities can be challenging (Viscusi and Zeckhauser 1996). Then, in line with the previous points, it is important to account for this potential bias at the specification stage of the primary study. Indeed, the use of RP techniques does not allow for an explicit presentation of risk levels. Moreover, if at the specification stage elements affecting perception can be accounted for, it can also be interesting to differentiate among levels of risks, or among risk and safety. Indeed it would be interesting to test if loss aversion is accounted for differently than taste for safety, as could be expected (Kahneman and Tversky 1979).

5. Concluding remarks

The purpose of this article was to explore the determinants of the implicit price of the risk of flooding. We carried out a meta-analysis on estimates resulting from the application of hedonic price models. The sample was made up of 16 studies and 86 points. Two effect sizes have been explored: the relative change in the price of a house located in a floodplain when compared to a house located outside a floodplain, and this relative change in price per level of risk. Specific attention has been paid to the possibility of multi-collinearity problems in the data. Meta-regression techniques have been applied; the dependent variable (effect size) has been regressed on selected covariates describing the research design, income level and covariates of the primary studies, the year of publication of the primary study and the level of flood risk. It appeared that data was heterogeneous and no publication bias has been identified; the so-called mixed effects model appeared to be the most appropriate to describe the relations between the effect size and the covariates.

It appeared that the choice of explanatory variables of hedonic price functions affects the variability between estimates, as well as the type of data. The level of income has been identified as a means to protect from risk vulnerability, and it has been observed that the implicit price of flood decreased over time. Factors related to the exploitation of spatial characteristics of the data such as the use of a GIS did also play a role. Finally, it appeared that specific attention has to be paid to the perceived level of risk; elements affecting the perception of individuals on the effective risk of flooding and allowing them to update their perception of the level of risk explained variability between estimates.

These elements should be treated with caution when using a hedonic price model to estimate the implicit price of any environmental risk.

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Appendix 1: list of selected studies

First author	Year	Location	Nb of estimates	Proba of risk	Elements potentially affecting perception	Change in price coefficient	Number of observations	Time span
Afua Dei Tutu	2002	Pitt County, North Carolina	3	0.01	Floyd, 1999	3E-05 to 9.8E-05	5122	4.5
Bartosova	1999	Wawatosa and Milwaukee, Wisconsin	7	0.002 to 0.01	Flood, 1997	-0.08 to 0.14	1431	3.5
Bialeszewski	1990	Homewood, Alabama	1	0.01		0.000162	93	1
Bin	2003	Pitt County, North Carolina	3	0.01	Floyd, 1999	-0.08 to -0.04	8375	10
Donnelly	1989		1	0.01		-0.12	325	2
Fridgen	1999	Fargo and Moorhood, North Dakota and Minnesota	4	0.002 to 0.01		-0.1 to 0.03	3783	3.6
Hallstrom	2004	Lee County, Florida	8	0.01	Andrew, 1992; changes in the insurance programme, 1994	-0.09 to 0.15	4506	18
Harrison	2001	Aluacha, Florda	4	0.01	National Flood Insurance Programme reform	-0.04 to -0.01	8673 to 29881	18
MacDonald	1987	Monroe, West Monroe, Ouachita parish, Louisiana	6	0.01	Flood, 1982 (localised in the parish)	-0.18 to -0.06	60 (parish) and 217 (all sample)	0.25
MacDonald	1990	Monroe, Louisiana	6	0.01	Flood, 1978, 1983 (localised in the parish)	-0.2 to -0.07	64 (parish) and 301 (all sample)	0.5
Shabman	1998	Roanoke, Virginia	1	0.01		-0.03	82	11
Shilling	1989	Bâton Rouge, Louisiana	1	0.01		-0.08	114	1.2
Skantz	1987	Houston, Texas	7	0.01	Flood, 1979	-0.06 to -0.01	124 to 183	4
Speyrer	1991	New Orleans, Louisiana	4	0.01	Flood 1978, 1980, 1983; California natural hazard disclosure law, 1998	-0.2 to -0.04	769 to 1229	16
Troy	2003	California	4	0.01		-0.23 to 0.01	17318	3
US Army Corps of Engineers	1998	Abilene, Texas; Pike County, Kentucky	26	0.002 to 0.2		-0.27 to 0.16	280 to 478	1 to 5

Appendix 2: complete list of explanatory variables

The full set of explanatory variables is made up of 4 vectors.

***D**: vector of variables describing the research design*

- the time span of the original sample, and its median year
- the date of publication of the original study
- model specification: the use of a transformation on the dependent variables (Box Cox or semilog, a linear model being the default one); the use of weighted least squares; the estimation of (White) robust standard errors
- type of data: cross section data, in opposition to time series or panel data
- data in the primary study was spatially identified (geo-coded)
- the fact that the dependent variable in the primary study was observed or assessed

***R**: vector of variables describing the risk of flooding*

- the objective probability of risk, that is to say the inverse of the expected frequency of flood in years
- elements that might influence the subjective probability via a modification of perception, such as the fact that the house is sold after the recent occurrence of a disaster, or after a change in insurance patterns

***V**: vector of indicative variables describing the variables included in the original HPM*

- accessibility: covers the variables measuring distance between the house sold, and the nearest highway, major road or airport
- comfort: indicates that the house has either a fire place, a hard wood floor, a pool, a gas heating, central heating, central air-conditioning, and the number of bedrooms
- distance to amenity: relates to the variables measuring distance between the house sold and a business centre, a centre of employment, a park or a golf
- distance to water: covers the variables measuring distance between the house sold and a river, the coast, a creek or a stream, a lake or a canal
- financing: indicates if the house was financed by a conventional loan
- insurance: corresponds to the flood insurance premium
- market: indicates the delay before the house was sold

- neighborhood: every kind of characteristics describing the neighborhood, such as a high endowment in services, educational matters (the proportion of high school graduates, the teacher student ratio, the ranking of district school), some population characteristics (age, employment rate, level of income, density, percentage of poverty, proportion of Hispanics or other races), or even the distance to a Starbuck coffee bar
- pollution: the pollution level
- quality: elements that give indications on the quality of the house such as the age of the house, the nature of the basement, the quality of the walls (in plaster), the presence of a face brick
- size: the size of the house in terms of number of bedrooms, of the presence of a garage attached, and area (lot size and living area). However, because such a variable was always included in original HPM, this dummy has the value 1 for all the observations, and is not included in the vector V
- tax level

L*: vector of variables catching some locational characteristics*

- the household median income per county (constant 2003 dollars; U.S. Census Bureau, Current Population Survey, Annual Social and Economic Supplements), computed from: $$\frac{1}{2}\left(\frac{incomecounty_{1989} * incomeUSA_{samplemedianyear}}{incomeUSA_{1989}} + \frac{incomecounty_{1979} * incomeUSA_{samplemedianyear}}{incomeUSA_{1979}}\right)$$
- the fact that the original HPM was estimated in a county located in the Southern (Louisiana, Texas, North Carolina, Florida, Alabama), Western (California) or Northern (North Dakota, Minnesota, Wisconsin) part of the United States

Appendix 3: Multi-collinearity between explanatory variables

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X
A	1	0	0.12	0	0.029	0.308	0.194	0.21	0.063	0.118	0.176	0.148	0	0.273	0.125	0	0	0	0	0	0.267	0.2	0.222	0
B	0	1	0.56	0	0.735	0.462	0.355	0.323	0.469	0.706	0.824	0.63	0.889	0.636	0.667	0.667	0	1	0	0.5	0.467	0.3	0.259	0.5
C	0.188	0.438	1	0	0.324	0.481	0.355	0.177	0.391	0.618	1	0.519	0.778	0.636	0.583	0.333	0	1	0	0.75	0.317	0.2	0.111	1
D	0	0	0	1	0	0	0	0.194	0.094	0	0	0	0	0	0	0	0	0	0.444	0.25	0.033	0.4	0.444	0
E	0.063	0.781	0.44	0	1	0.5	0.226	0.323	0.469	0.588	0.412	0.481	1	0.727	0.417	0.667	0	1	0	0.5	0.5	0.267	0.222	0.5
F	1	0.75	1	0	0.765	1	0.548	0.452	0.563	1	1	1	0.889	1	1	0.333	0	1	0	0.75	0.767	0.5	0.444	1
G	0.375	0.344	0.44	0	0.206	0.327	1	0.5	0.391	0.324	0.647	0.148	0.778	0.909	0.167	0	1	1	0.556	0.5	0.283	0.067	0	0.5
H	0.813	0.625	0.44	1	0.588	0.538	1	1	0.656	0.412	0.647	0.259	1	1	0.167	0.667	1	1	1	0.75	0.633	0.767	0.778	0.5
I	0.25	0.938	1	0.5	0.882	0.692	0.806	0.677	1	0.882	1	0.852	1	0.727	0.917	1	1	1	0.778	0.875	0.717	0.6	0.556	1
J	0.25	0.75	0.84	0	0.588	0.654	0.355	0.226	0.469	1	1	1	0.778	0.636	1	0.333	0	1	0	0.75	0.467	0.233	0.222	0.5
K	0.188	0.438	0.68	0	0.206	0.327	0.355	0.177	0.266	0.5	1	0.37	0.778	0.636	0.417	0	0	1	0	0.5	0.217	0.1	0.037	0.5
L	0.25	0.531	0.56	0	0.382	0.519	0.129	0.113	0.359	0.794	0.588	1	0	0	1	0.333	0	0	0	0.25	0.417	0.233	0.222	0.5
M	0	0.25	0.28	0	0.265	0.154	0.226	0.145	0.141	0.206	0.412	0	1	0.636	0	0.083	0	1	0	0.5	0.083	0	0	0
N	0.188	0.219	0.28	0	0.235	0.212	0.323	0.177	0.125	0.206	0.412	0	0.778	1	0	0	0	1	0	0.5	0.117	0	0	0
O	0.188	0.5	0.56	0	0.294	0.462	0.129	0.065	0.344	0.706	0.588	0.889	0	0	1	0.333	0	0	0	0.25	0.367	0.233	0.222	0.5
P	0	0.25	0.16	0	0.235	0.077	0	0.129	0.188	0.118	0	0.148	0.111	0	0.167	1	0	0	0	0.25	0.167	0.133	0.185	0
Q	0	0	0	0	0	0	0.452	0.226	0.219	0	0	0	0	0	0	0	1	0	0.556	0	0.067	0	0	0
R	0	0.219	0.28	0	0.206	0.135	0.226	0.113	0.109	0.206	0.412	0	0.778	0.636	0	0	0	1	0	0.5	0.05	0	0	0
S	0	0	0	0.667	0	0	0.323	0.29	0.219	0	0	0	0	0	0	0	0.714	0	1	0	0	0.267	0.296	0
T	0	0.125	0.24	0.167	0.118	0.115	0.129	0.097	0.109	0.176	0.235	0.074	0.444	0.364	0.083	0.167	0	0.571	0	1	0	0.067	0.111	0
U	1	0.875	0.76	0.167	0.882	0.885	0.548	0.613	0.672	0.824	0.765	0.926	0.556	0.636	0.917	0.833	0.286	0.429	0	0	1	0.667	0.593	1
V	0.375	0.281	0.24	1	0.235	0.288	0.065	0.371	0.281	0.206	0.176	0.259	0	0	0.292	0.333	0	0	0.444	0.25	0.333	1	0.963	1
W	0.375	0.219	0.12	1	0.176	0.231	0	0.339	0.234	0.176	0.059	0.222	0	0	0.25	0.417	0	0	0.444	0.375	0.267	0.867	1	0
X	0	0.063	0.16	0	0.059	0.077	0.065	0.032	0.063	0.059	0.118	0.074	0	0	0.083	0	0	0	0	0	0.067	0.133	0	1

Vector D

Specification issue

A BoxCox transformation
B Semilog transformation
C Use of a GIS

Type of data

D Assessed selling prices
E Time series or panel data

Vector V

Primary explanatory variables

F Comfort
G Neighborhood
H Omission bias neighborhood
I Quality
J Accessibility or distance
K Accessibility
L Distance to amenity
M Market
N Tax
O Distance to water
P Finance
Q Insurance
R Pollution

Vector R

Definition of risk

S Very high probability
T Very low probability
U 100-year floodplain

Perception issue

V After a change in available information
W After the occurrence of a flood
X After a change in insurance disclosure