Exploring the price dynamics of flood risk on the housing market: A meta-analysis approach

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ABSTRACT

The existing literature on the effect of flood risk on house prices produces inconsistent findings. The purpose of this paper is to analyze the various findings in the literature in order to determine the overall effect and explain the study-to-study variation. This is accomplished through conducting a meta-analysis of 14 relevant papers published between 2013 and 2023. A total of 191 extracted estimates demonstrate a price difference that extends from -84% to +41.4%. The analysis shows that flood risk discount is greatest shortly after a flood and diminishes over time. Houses in coastal floodplains command a premium due to a failure to separate the effect of being in a coastal floodplain from the amenities associated with it. Controlling for time elapsed since the most recent flood, study characteristics, and contextual factors, the meta-regression results reveal that a property in a 100-year inland floodplain is associated with a 4.7% price discount.

Keywords: Meta-analysis, meta-regression analysis, flooding, flood risk, house prices

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1. INTRODUCTION

1.1. Motivation

The effects of climate change are increasingly becoming more visible all around the world. In 2023, many countries experienced the warmest and wettest year on record according to the World Meteorological Organization (WMO, 2023). Natural disasters are increasing in frequency due to extreme weather, and it is estimated that they result in direct asset losses of about $300 billion annually (Rentschler & Salhab, 2020). Overall, disaster costs have been rising for several decades as a result of increased exposure, vulnerability of people and infrastructure, and climate change (Ebi et al., 2021).

Flooding is the world's most frequent and costly natural disaster (Koning et al., 2019). To mitigate the damage caused, it is essential to manage development in flood-prone areas. The threat of floods is a global reality; it is estimated that 2.2 billion people, or 29 percent of the world population live in areas that would experience some level of inundation during a 1-in-100-year flood event, and 19 percent of the world's population, around 1.47 billion people, are directly exposed to flooding depths of more than 0.15 meters, which poses a significant risk to lives, particularly for vulnerable population groups (Rentschler & Salhab, 2020).

In an efficient housing market with complete information, flood risk is capitalized into property prices. This implies that because of the possibility of flood damage, the value of a property inside a floodplain is less than the value of identical property outside the floodplain (Hino & Burke, 2021). Properties inside floodplains might experience reduced desirability, higher insurance costs and more property damage and maintenance. The price differentials between these properties should reflect the expected loss associated with the flood occurring (MacDonald et al., 1990). The Dutch independent institution, known as the 'Autoriteit Financiële Markten' (AFM) or Financial Markets Authority in English, asserts that climate risks are currently not adequately integrated into housing prices (Clahsen, 2023). This is because buyers are either unaware of the risks or unable to assess them, imposing a significant financial risk for homebuyers. Additionally, Baldauf et al. (2020) find that differences in beliefs about climate change are reflected in property prices. Proposing a solution to enhance transparency and facilitate more efficient pricing of properties, the AFM suggests implementing a 'climate label' for residential properties (Clahsen, 2023).

The effect of flood risk on property values has been the subject of numerous studies, but the findings of these studies have been conflicting regarding the direction and magnitude of this impact (Belanger et al., 2018). On the one hand, many papers report a discount for houses in flood plains. On the other hand, several articles claim that being located in a flood plain has no effect on home prices or even comes at a premium (Bin & Kruse, 2006; Morgan, 2007). In order to identify the underlying factors behind these variations and to determine the true effect of flood risk on property values, this study will employ a meta-analysis.

1.2. Academic relevance

The existing literature on the impact of flood risk on house prices yields contradictory results. An inventory of the literature compiled by Daniel et al. (2009) reveals that willingness to pay estimates range from -52 to +58% of the average property price located within the 100-year floodplain. The 100-year floodplain is an area with a 1% annual chance of flooding and is the flood zone contour used in most studies to define the risk level. The literature provides several reasons for the variability in estimates. One contributing factor is the internal variation of flood risk within the 100-year floodplain. The delineation of the 100-year floodplain relies on the risk level at its boundary, resulting in different flooding probabilities for individual properties within the floodplain (Bartosova, 2000; Highfield et al., 2013; Turnbull, 2013). Next to that, depending on the type of flood risk as well as the stages of the housing market, the mix of capitalization in price relative to liquidity can change (Turnbull et al. 2013). Moreover, controlling for amenities related to living in a flood-prone area is problematic. This is particularly true for coastal areas, where residents place a higher value on amenities associated with nearness to the coast, which may result in a price premium (Bakkensen & Barrage, 2017). Finally, Daniel et al. (2009) and Beltrán et al. (2018) highlight differences in estimates before and after a flood event. This divergence is attributed to an increased awareness of risk, typically observed following a hazard, as emphasized by Hallstrom and Smith (2005).

Meta-analysis can be used to explain study-to-study variation when numerous independent studies have been conducted on a specific topic with differences in findings (Stanley, 2001). In the fields of medicine and economics, meta-analysis is a well-known approach (Stanley, 2001; Daniel et al. 2009). However, it is not often used in real estate economics when addressing flood risks. The only studies on flood risk discount that use meta-analysis are those by Daniel et al. (2009) and Beltrán et al. (2018). In their meta-analyses, they discover substantially different coefficients: Daniel et al. (2009) find that a location inside a 100-year floodplain is associated with a price difference of -0.6%, whereas Beltrán et al. (2018) find that this is -4.6%. One possible explanation for this disparity is that Daniel et al. (2009) include coastal and inland studies in the same analysis, whereas Beltrán et al. (2018) considers this problematic and excludes coastal estimates.

The prior meta-analyses included studies up to the year 2013. In an effort to expand and update these findings, this research seeks to reassess the analysis conducted by Beltrán et al. (2018), incorporating all relevant studies published after 2013.

1.3. Research problem statement

The research aim of this study is to analyze the relationship between flood risk and house prices by conducting a meta-analysis. Meta-analysis is an approach based on statistical methods designed to summarize the variation in findings across multiple studies (Walker et al., 2008). By combining studies, it increases the overall sample size and, as a result, enhances the statistical power. Meta-regression analysis is a type of meta-analysis that is specifically designed to examine empirical economic research (Stanley, 2001). In meta-regression analysis, the dependent variable is a summary statistic, a regression parameter derived from each study, and the independent variables can be characteristics of the method, design, and data used for different studies. Meta-regression analysis can assess the degree to which a given choice of method, design, and data affect the findings presented (Stanley, 2001).

The central research question is:

"What is the overall effect of flood risk on house prices?"

The research question will be addressed through a meta-regression on the relevant literature, aided by the following set of sub-questions:

1) *How does flood risk affect house prices?*

By conducting a literature review, the first question will be addressed. The meta-analyses of Daniel et al. (2009) and Beltrán et al. (2018) will serve as the starting point for the literature review, as they comprehensively evaluate most of the relevant literature on the impact of flood risk on house prices. Further investigation will be conducted into studies that yield contradictory findings to explore the factors contributing to these discrepancies.

2) *What factors explain variation in the effect size of flood risk on housing prices as reported by existing studies?*

First, relevant studies will be selected from a standard database. From these studies, the summary statistic will be selected and effect sizes together with their standard errors will be computed. Each estimate will involve the addition and coding of independent variables, also known as moderator variables. These variables are derived from previous meta-analyses, supplemented by additional variables deemed relevant after a comprehensive review of the literature. In the meta-regression, it should become apparent whether and how the effect sizes are influenced by the independent variables.

The structure of the remaining sections in this paper is outlined as follows: Section 2 provides an overview of hedonic pricing theory, reviews relevant literature on the impact of flood risk on house prices, and outlines hypotheses related to the research questions. In Section 3, the methods for data collection and conducting meta-analysis are detailed. Section 4 presents and discusses the results of the subsample meta-analysis and meta-regression, including checks for robustness. Finally, Section 5 concludes.

2. THEORY, LITERATURE & HYPOTHESES

2.1. Hedonic pricing

The hedonic price model, which is based on the foundational works of Lancaster (1966) and Rosen (1974), has been widely used in scientific research on housing markets. According to the hedonic pricing theory, the price of a house is determined by the consumer's willingness to pay for specific characteristics associated with the house (Chau & Chin, 2003). This implies that the characteristics of a property are valued rather than the property itself (Morgan, 2007). These characteristics incorporate structural attributes of the property as well as neighborhood and locational features. Structural attributes include characteristics such as the age of the house, size, number of rooms, type of house, and so forth. Crime rates, median household income, proximity to water, parks, or shopping centers, as well as flood risk, are examples of neighborhood and locational characteristics (Bartosova, 2000). Equation (1) describes the hedonic price function for properties with regard to flood risk.

$$P = f(X, F) \tag{1}$$

Here, the price of a property, P, is described as a function of the previously mentioned characteristics, and the flood risk variable F (Bartosova, 2000). The model assumes that the housing product is homogeneous, that the market operates under perfect competition, that buyers and sellers have perfect information, and that the market is in equilibrium (Chau & Chin, 2003). A rational consumer will locate within the flood risk area only if they are compensated for potential losses (MacDonald, 1987). Therefore, properties exposed to risk are expected to be priced at a discount compared with properties that are not, all else being equal. The expected losses from flooding should be equal to the price discount (Morgan, 2007).

2.2. Variation in flood risk effects across studies

As previously noted, research exploring the relationship between flood risk and house prices has produced mixed and inconclusive results. This becomes most evident from previous meta-analyses (Daniel et al., 2009; Beltrán et al., 2018), as they analyze and combine the results of all relevant studies to arrive at an overall effect. Daniel et al. (2009) have 117 point estimates from 19 primary studies for the relative change in house price for houses located in a 100-year floodplain in their meta-sample. These estimates range from -52% to +58%, with approximately 70% of the estimates being negative and an average of around -2%. Beltrán et al. (2018) retrieved 349 estimates from 37 studies, ranging from -75.5% to +61%. In their meta-sample, 33 of 37 studies report an average discount for floodplain houses. The average for all estimates is -6.1%. It is crucial to emphasize that this represents merely the mean of the estimates and does not capture the overall effect on property values located in a floodplain. The overall effect must be computed using meta-analysis with weights assigned to each estimate. Given that the majority of studies indicate a price discount, the literature reporting premiums for floodplain locations will be reviewed first.

Bin & Kruse (2006) conducted a study on the impact of flood hazard on residential property values in Carteret County, a coastal county in North Carolina. They discover a 5 to 10% discount for properties situated in an inland flood zone. Conversely, for properties located in coastal flood zones, an increase in property values is observed. They conclude that being situated within a coastal flood zone and proximity to coastal water are so intertwined that it is impossible to disentangle the two effects on property values. Morgan (2007) similarly identifies a price premium for properties situated within the floodplain. This research is conducted in Santa Rosa County in Florida, which also has a coastline. Subsidized flood insurance programs reduce expected flood losses. This can then lower homeowners' risk perception (Morgan, 2007). As a result, the amenities of living close to the coast may outweigh the risk associated with it. Consequently, floodplain properties may reveal a premium. Regression results incorporating a post-flood interaction term indicate a decrease in property values. This implies that the damage inflicted by a storm reinforced homeowners' perception of flood risk. The heightened perceived flood hazard diminishes the appeal of certain amenities associated with coastal living (Morgan, 2007).

The literature emphasizes the significance of risk awareness (Belanger et al., 2018). According to Samarasinghe & Sharp (2010), the discount associated with location in a flood zone is dependent on the availability of flood maps. This aligns with the findings of Belanger et al. (2018), who observe that extensive flood awareness campaigns have played a role in enhancing people's consideration of flood risk in the property market. Other studies argue that it is the occurrence of a hazard that leads to the increase in risk awareness and lower property prices in flood zones (Bin & Polasky, 2004; Hallstrom & Smith, 2005). The enhanced risk awareness is greatest immediately after the flood and decreases over time, eventually disappearing after five to six years. (Atreya et al. 2013; Bin & Landry, 2013). The decay in risk perceptions is consistent with Tversky's and Kahneman's theory of availability heuristic. The availability heuristic is a cognitive bias whereby people rely on readily available information or examples that come to mind easily when making decisions or forming beliefs (Bin & Landry, 2013). Atreya & Ferreira (2015) found that whether a property is actually inundated determines the discount after a flood event and that whether a property is situated in a floodplain or not makes no significant difference. Studies that do not account for whether or not houses in floodplains are also in the inundated area overestimate the information effect of a flood, claim Atreya & Ferreira (2015). Hino & Burke (2021) suggest that the real estate market's unique characteristics, which set it apart from the theoretical market where asset prices accurately reflect all relevant information, could be the cause of the inconsistent pricing of risk in property values. The differences in discounts as a result of people's risk awareness indicate a subjective assessment of the probability of a house flooding (Knuth et al., 2014).

The results from previous meta-regressions (Daniel et al., 2009; Beltrán et al., 2018) demonstrate a discount for location in a floodplain. Daniel et al. (2009) report a discount of -0.6%, while Beltrán et al. (2018) reveals a more substantial discount of -4.6%. Both studies discover differences in pre- and post-flood estimates, confirming that recent floods cause homeowners' perceptions of flood risk to change. Additionally, they observe that properties in coastal flood risk zones sell at a premium, resulting from the correlation between floodplain location and the amenities associated with coastal proximity. Finally, Beltrán et al. (2018) find that including a variable measuring time elapsed since the most recent flood has significant impact on the effect of flood risk on house prices.

This review of the literature shows that flood risk has a negative impact on house prices. The capitalization of flood risk in house prices is influenced by people’s perception of risk. The awareness of flood risk tends to rise due to new information, such as the availability of flood maps or actual flood events and diminishes over time.

2.3. Hypotheses

The literature provides a basis for formulating hypotheses related to the research questions. In addressing the main research question, the assumption is that the overall impact of flood risk on house prices in the studies within this meta-sample will closely resemble the overall effect identified in previous meta-analyses. The hypothesis is therefore formulated as follows:

H1: *The overall effect of flood risk on house prices is negative and will be around the same order of magnitude as the discounts found in previous meta-analyses.*

The following is the hypothesis for sub-question 2:

H2: *The variability in the effect size can be attributed to factors such as the geographical regions where the primary studies were conducted, the flood history of those areas impacting people's risk perception, and various study characteristics, such as the consideration of amenities in the analysis.*

3. META-ANALYSIS: DATA & METHODS

The process of conducting a meta-analysis involves the following steps (Stanley, 2001). The first step is to include all relevant studies on the subject from standard databases using a precise combination of keywords. The next step entails selecting a summary statistic and transforming it into a common and comparable metric. This metric, referred to as the effect size, will function as the dependent variable in the meta-regression analysis. The third step is choosing moderator variables and coding them, these will be the independent variables in the regression. The final steps are conducting a meta-regression analysis and subjecting this to specification testing (Stanley, 2001).

Each section in this chapter delineates a separate step in the process of doing a meta-analysis. Since this study builds upon previous research by Daniel et al. (2009) and Beltrán et al. (2018) many of the same methods are used in this research. Maintaining consistency in the methods employed ensures a more effective comparison of results and allows for a robust examination of the evolution or continuity of patterns over time.

3.1. Data collection for meta-analysis

The first step involves the inclusion of all relevant studies. The databases accessible and used to collect the population of studies for this research were SmartCat and Google Scholar. This study only looked for papers published after 2013, as the Beltrán et al. (2018) meta-sample includes all relevant studies up until then. The following Boolean search strategy is copied from Beltrán et al. (2018):

(Flood* OR Inundat* OR Hurricane*) AND (Propert* OR Hous* OR Resident* OR “Real Estate”)

This word combination yielded a large number of results; however, many of the studies found were not useable. Consequently, alternative methods were explored by incorporating additional keywords into the search strategy, which were Hedonic* and Floodplain. Every discovered paper underwent scanning based on its title, abstract, introduction, methodology, and tables. The papers that appeared to be relevant for the meta-sample were saved for further examination and were later fully analyzed. For the studies to be considered sufficiently homogeneous to be included in the meta-sample, they must meet the following requirements (Daniel et al., 2009; Beltrán et al., 2018):

i. An econometrically estimated Hedonic Price Function is used to derive estimates, this should be the standard hedonic model or a Difference-in-Differences model.
ii. Estimates must be reported as a percentage of average house prices, after recalculation if necessary.

iii. Flooding risk should be reflected by a dummy variable which indicates location within the 500-year or 100-year floodplain.

These requirements led to the exclusion of particular studies. In some cases, the flood risk is not explicitly indicated as location in the 500-year floodplain or the 100-year floodplain. Egbenta et al. (2015), for instance, describe the floodplain as "an area that is likely to flood in the event of the river overflowing its bank", but no probability is given. Bakkensen et al. (2019) do provide the probability for flood risk. However, their study design designates the 100-year flood zone as the treatment group and the 500-year flood zone as the control group. This approach yields estimates that are not directly comparable with the rest of the estimates. Studies that specify flood risk as distance to the river or elevation are also excluded (Rajapaksa et al., 2016; Cohen et al., 2021; Hsieh, 2021). Hirsch and Hahn's (2018) model provides a discount for floodplain properties in euros, but no average house prices are provided, making it not possible to calculate a percentage. Alternative estimation approaches, such as the linear mixed effects model used by Belanger and Bourdeau-Brien (2018) or the repeat sales model used by Beltrán et al. (2019), are also left out. Repeat sales models specifically capture the price changes of individual properties over time in response to certain events. However, they do not provide information on the price differentials between different properties. Consequently, the computation of a price differential using repeat sales models is not possible (Beltrán et al., (2018).

The final database is made up of 14 studies with a total of 191 estimates, as can be seen in Table 1. There is a wide range of estimates between studies, ranging from 2 to 40. Studies that have a relatively large number of estimates often employ difference-in-differences specifications and use different control groups in their models. The majority of studies were conducted in the United States, with the exceptions of Pommeranz & Steininger (2020) in Germany and Nguyen et al. (2022) in New Zealand. The publication year of the studies spans from 2015 to 2023. On average, most studies find that houses in floodplains sell for less, except for Nyce et al. (2015) and Atreya & Czajkowski (2019), which are studies conducted in areas with a coastline. The mean effect size for all studies, -5.2%, closely aligns with the meta-sample average of -6.1% reported by Beltrán et al. (2018). The standard deviation of 0.163 indicates a relatively large amount of variability in effect sizes. The estimates range from a -84% discount to a 41.4% premium.

TABLE 1: Summary of studies and their estimates included in the final database

No.	Authors	Year	Country	Location[2]	Estimates	Effect Size (T)			
						Mean	S.D.	Min.	Max.
1	Atreya & Ferreira	2015	US	Georgia	15	-0.122	0.331	-0.626	0.414
2	Lee	2015	US	Georgia	6	-0.015	0.062	-0.100	0.091
3	Nyce et al.	2015	US	Florida	24	0.096	0.087	0.007	0.204

4	Meldrum	2016	US	Colorado	12	-0.044	0.055	-0.150	0.015
5	Zhang	2016	US	ND, MN	40	-0.089	0.088	-0.360	0.014
6	Atreya & Czajkowski	2019	US	Texas	12	0.148	0.147	0.004	0.353
7	Zhang & Leonard	2019	US	ND, MN	28	-0.086	0.071	-0.274	0.019
8	Hennighausen & Suter	2020	US	Colorado	8	-0.068	0.059	-0.190	0.011
9	Pommeranz & Steininger	2020	GER	Dresden	2	-0.058	0.001	-0.059	-0.057
10	Yi & Choi	2020	US	Iowa	16	-0.188	0.265	-0.840	0.095
11	Catma	2021	US	SC	2	-0.164	0.008	-0.170	-0.159
12	Miller & Pinter	2022	US	OR, CO, ND	12	-0.047	0.063	-0.157	0.094
13	Nguyen et al.	2022	NZ[1]	Dunedin	12	-0.061	0.011	-0.079	-0.046
14	Livy	2023	US	Ohio	2	-0.165	0.041	-0.194	-0.136
	Overall				**191**	**-0.052**	**0.163**	**-0.840**	**0.414**

Note here that effect sizes have already been calculated. [1] NZ = New Zealand, [2] ND = North Dakota, MN = Minnesota, SC = South Carolina OR = Oregon, CO = Colorado

3.2. Calculating effect sizes and standard errors

The second step involves transforming the estimates from the primary studies into a comparable metric, the effect size. The effect size will function as the dependent variable in the meta-regression. Additionally, for each effect size, the corresponding standard error must be computed, determining the weight assigned to the estimate in the regression analysis. The calculation of effect sizes and their standard errors relies on the methodology and regression equation applied in the primary studies. The following paragraphs detail the steps involved in calculating these values for different models.

A semi-log functional form for the hedonic price function is used consistently by all studies in the meta-sample. Equation (2) shows the basic hedonic price function without interaction variables.

$$\ln(P_i) = \beta_0 + \beta_1 FP_i + \sum_{j=1} \beta_j X_{ij} + \varepsilon_i \qquad (2)$$

Here, $\ln(P_i)$ is the natural log of house prices.
β_0 is the intercept.
FP is a dummy variable that takes the value of 1 if the property sale is within the designated floodplain area, β_1 is the corresponding coefficient.
The operator $\sum_{j=1} \beta_j X_{ij}$ represents the summation of other independent variables used in the primary studies, such as housing and locational characteristics.
ε_i is the error term.

The effect size of interest is the house price difference associated with location in a flood zone. The effect size is referred to as T, with s_t the associated standard errors (Daniel et al., 2009; Beltrán et al., 2018). With a semi-log functional form, the effect size T equals β_1, the coefficient for the floodplain dummy. The standard error s_t is then also the standard error for the coefficient β_1, which is typically provided in the studies' regression tables. There are also studies in the meta-sample that use spatial econometric models. Beltrán et al. (2018) calculated the total effect for those estimates. However, for the sake of simplicity, and considering that the results are largely unaffected, this research only uses the direct effect.

Besides the basic model outlined in equation (1), studies frequently employ DiD models to assess the impact of a recent flood on housing prices. This framework contains two time periods, "pre" and "post" and two groups, "treatment" and "control" (Goodman-Bacon, 2021). Equation (3) shows the hedonic price function for a DiD model.

$$\ln(P_{it}) = \beta_0 + \beta_1 FP_i + \beta_2 Flood_{it} + \beta_3 (FP_i * Flood_{it}) + \sum_{j=1} \beta_j X_{ij} + \varepsilon_{it} \quad (3)$$

The variable $Flood$ is a dummy variable that takes the value of 1 if the property transaction happened after a flood event. β_2 therefore measures the relative difference in sale prices for all houses sold after the flood. β_1 measures the difference in house prices between the floodplain and the control group before any flood. β_3 reflects the additional impact on house prices within the floodplain after the flood event. β_1 and β_3 can then be added to determine the effect size T for houses in a floodplain that were sold after a flood (Beltrán et al., 2018). To calculate the standard error for the sum of two coefficients, the following formula is used:

$$SE(\beta_1 + \beta_2) = \sqrt{SE(\beta_1)^2 + SE(\beta_2)^2 + 2 * \rho * SE(\beta_1) * SE(\beta_2)} \quad (4)$$

ρ is the correlation between the two coefficients β_1 and β_2. However, in many studies, the correlation is not provided. Instead, a value of -0.9 or +0.9 is used. The sign is positive when β_1 and β_2 share the same sign, and negative when they do not (Daniel et al., 2009).

Figure 1 depicts the funnel plot illustrating the relationship between effect sizes and their precision. The pseudo 95% confidence intervals are also plotted. A funnel plot is commonly used to visually explore publication bias. In the absence of publication bias and heterogeneity, the anticipated pattern would involve the majority of studies being randomly dispersed within the confidence interval region, resembling an inverted funnel shape (StataCorp, 2023). The figure makes it evident that there are a substantial number of estimates outside the 95% confidence interval. The results of an Egger et al.

(1997) regression asymmetry test reveal significant publication bias, suggesting a tendency to report more negative impacts. Daniel et al. (2009) and Beltrán et al. (2018) also find evidence of publication bias. However, Daniel et al. (2009) state that publication bias may be mistaken for observable and unobservable heterogeneity among the effect sizes. Between-study heterogeneity is another common reason for an asymmetrical funnel plot (StataCorp, 2023). Additional information regarding effect sizes, confidence intervals, and heterogeneity statistics can be found in the forest plot included in the appendix.

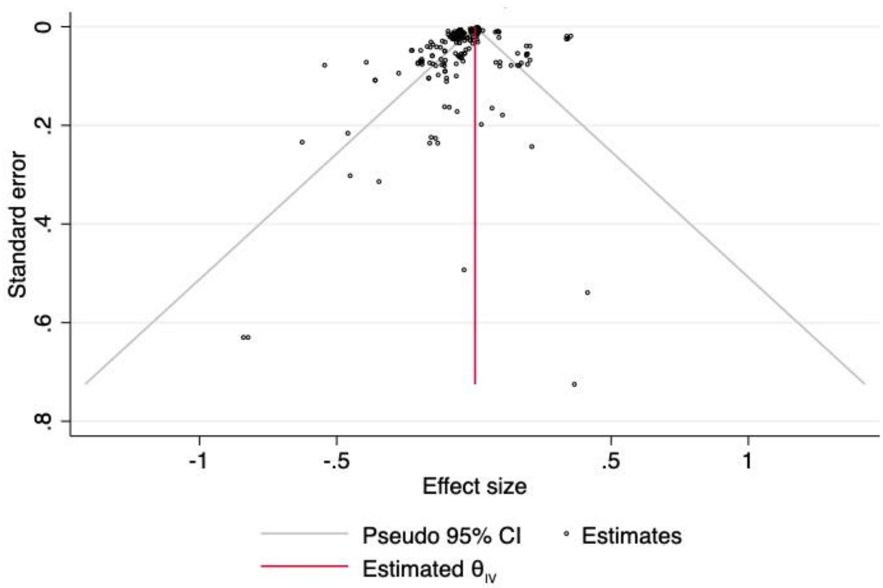

FIGURE 1: Funnel plot of the 191 effect sizes against their standard error

Notes: Random effects model, REML method

3.3. Incorporating and coding moderator variables

The third step is to incorporate and code the independent variables for each estimate. These are referred to as "moderator variables," indicating study characteristics that are thought to be consequential (Stanley, 2001). Dummy variables should be coded for the use of different data sets and modelling choices. However, not every minor study characteristic can be coded and analyzed. In this study, moderator variables are selected based on a review of previous meta-analyses and the existing literature on flood risk and property prices. The specific attributes are extracted from the primary studies' methodology, descriptive statistics, and regression tables.

Table 2 displays the variables included in the meta-analysis along with their corresponding summary statistics. The variables incorporated in the regression are mostly the same as the variables included in Beltrán et al. (2018), except for certain omitted variables that were not applicable or relevant to the data in the meta-sample. The following variables are left out: dd_afterlaw, linear, box_cox, and published. The variable “dd_afterlaw” is a dummy variable that takes the value of 1 if the effect is from a DiD model following a change in regulation for floodplain-designated areas, which was not the case for any of the primary studies' estimates. “Linear” and “box_cox” relate to specifications of the hedonic price function. However, as mentioned previously, only semi-log functional forms are utilized. The variable “published” acts as a dummy variable indicating studies published in refereed journals. As all studies in this context meet this criterion, the variable is not considered in the analysis. Furthermore, additional variables were introduced in this model. These variables are: “time_fe” and “near_miss”. Most studies did not convert prices to a constant measure. However, many did incorporate month and/or year dummies to capture the seasonal effect and macroeconomic impact over time (Zhang, 2016). This accounts for the introduction of an additional dummy variable, which is the variable “time_fe”. Beltrán et al. (2018) include the variable "flooded" because the price discount is expected to be greater for inundated properties following a flood because of a change in risk perception. This is different for properties in flood zones that were not inundated as homeowners respond better to what they have visualized (Atreya & Ferreira, 2015). Consequently, the dummy variable "near miss" for properties in flood zones that were not inundated has also been included.

The months since the most recent major flood are calculated for each estimate. This implies that, for each study area, the flood history is examined or retrieved with the help of Google. The months elapsed is calculated by subtracting the date of the most recent flood from the median sample year in the primary study. Months elapsed are calculated for both pre- and post-flood estimates in studies using DiD models, which explains the large variation in values for the variable. This variable is of considerable interest, as it plays a crucial role in accounting for changes in flood risk perception based on the time elapsed since the last flood event (Beltrán et al., (2018).

The main variable of interest is (*Floodrisk*). This variable is coded as 0.01 for properties situated in a 100-year floodplain and as 0.002 for properties in a 500-year floodplain. In the regression, this variable's coefficient can be interpreted as the percentage discount for houses located in the 100-year floodplain (Beltrán et al., 2018).

The next set of moderator variables accounts for the context of the primary studies. The mean square footage and square price of houses in the studies are obtained from descriptive tables, after which the natural logarithm is calculated. If the values are initially provided in meters or euros, a conversion is applied. While nearly half of the estimates involve post-flood dummies, only a small fraction provides information about the actual inundation of properties. Around 20% of the estimates come from studies conducted in areas with a coastline. The majority of studies incorporate variables in their regression models to account for water-related amenities. The median sample year for all studies in the meta-sample is approximately 2007, reflecting a difference of around twelve years compared to the median sample year in Beltrán et al. (2018). The time span of property transaction data in the studies varies from 6 to 23, with a mean time span of 11.77.

TABLE 2: Meta-analysis descriptive statistics

Variables	**Description**	**N**	**Mean**	**S.D.**	**Min.**	**Max.**
Dependent variable						
Effect Size (T)	Relative price differential for floodplain location	191	-0.052	0.163	-0.840	0.413
Flood risk perception						
months	Number of months since previous major flood	191	178.7	202.2	6	852
Flood risk						
Flood Risk	Variable = 0.01 if the effect refers to the 100-year floodplain and 0.002 for a 500-year floodplain	191	0.009	0.003	0.002	0.01
Study context						
logfeet	Natural log of the mean square feet of the properties per study	191	7.39	0.30	6.01	8.18
logprice	Natural log of the mean price of the houses per study in US dollars	191	12.12	0.55	10.82	14.11
flooded	Dummy = 1, if the effect refers to flooded properties	191	0.047	0.212	0	1
scnd_flood	Dummy = 1, if the effect refers to a second flood	191	0.063	0.243	0	1
near_miss	Dummy = 1, if the effect refers to properties that were not inundated during a flood	191	0.047	0.212	0	1
dd_after	Dummy =1, if the effect corresponds to a post-flood DID estimate.	191	0.408	0.493	0	1
coast	Dummy = 1, if the study area has a coastline	191	0.199	0.400	0	1
Control variables of study						
amenities	Dummy = 1, if the study includes variables controlling for the amenity value of proximity to waterbodies	191	0.832	0.374	0	1
real_p	Dummy = 1, if the study converts prices to a constant measure prior to estimation	191	0.487	0.501	0	1
time_fe	Dummy = 1, if the study includes time-fixed-effects to control for time trends	191	0.948	0.223	0	1
Model characteristics						
spatial	Dummy = 1, if the effect corresponds to a spatial econometric model	191	0.393	0.49	0	1
dd_hpm	Dummy = 1, if the effect corresponds to a DID specification	191	0.691	0.463	0	1
Study characteristics						

med_sampleyear	The median sample year of the study	191	2006.8	4.53	1989	2014
time_span	The time span of the data covered in the study	191	11.77	4.90	6	23

After computing the effect sizes, standard errors, and coding moderator variables for each estimate, it is essential to declare the data as metadata in Stata. This can be done with the command "meta set es se", where es and se are the variables effect size and standard error. Once the data is declared as metadata, all subsequent meta commands will automatically use these variables in the meta-analysis.

3.4. Conducting meta-analysis and meta-regression

The final steps involve conducting the meta-analysis and meta-regression. Meta-analysis and meta-regression can be used to explore the between-study heterogeneity. In meta-analysis, estimates are grouped into different subsamples based on specific characteristics and an overall effect size is computed for each subsample. Analyzing overall effect sizes across various subsamples enables a thorough examination and potential clarification of the observed between-study heterogeneity (StataCorp, 2023). For each subsample, the number of estimates, the summary statistic with the 95% confidence interval, tau^2, the Q-statistic, and I^2 are reported. The summary statistic is the combined effect size, with H0 that the summary effect size is insignificantly different from zero. Tau^2 represents the between-study variance, a larger tau^2 indicates greater heterogeneity among studies. I^2 is the percentage of variability in effect sizes which is not caused by sampling error and is derived from the Q-statistic, which also assesses the presence of heterogeneity. H0 of the Q-stat is that all studies contained in the sample share a single effect size (Beltrán et al. 2018).

Random effects and fixed effects models are commonly used to combine effect sizes. Both models typically compute weight to estimates using the inverse-variance estimation method, with more precise estimates receiving more weight (Beltrán et al., 2018). Fixed effects models assume that all studies in the analysis share a common true effect size. In this case, this is implausible since studies differ in terms of both the methodology as well as the underlying population. In contrast, the random effects model permits the effect size to vary across different observations (Beltrán et al., 2018).

In their paper, Beltrán et al. (2018) address the issue of weighting, noting that models using random effects and fixed effects weighting schemes treat each observation as an individual study, resulting in improper weighting of studies that contribute multiple estimates of the effect size. In addition to the model that calculates weight using the inverse error-variance, they used an alternative weighting scheme. This approach determines the weight for each estimate by taking the square root of the mean sample size in the study and dividing it by the number of estimates per study. This method is also used to manually calculate the weight for each estimate in this study. The calculated weights have been incorporated into the database, enabling the execution of models using both weighting schemes.

The objective of the meta-regression is to explore and explain the relationship between the effect sizes and the moderators. The equation for the meta-regression is expressed as follows:

$$T_i = \beta_0 + \beta_1 Floodrisk_i + \beta_2 Months_i + \beta_3 X_{3i} + \ldots + \beta_{17} X_{17i} + \varepsilon_i \qquad (5)$$

Here, T_i is the effect size for the i^{th} estimate.
β_0 is the intercept.
β_1 is the coefficient for the variable flood risk, which, as previously stated, is interpreted as the percentage discount for houses located in the 100-year floodplain.
β_2 is the coefficient for the variable months, indicating the number of months elapsed since the previous flood event.
X_{3i}, ... X_{17i} represent the remaining moderator variables included in the regression.
ε_i is the error term.

In interpreting β_1, it is important to note the assumption made by Beltrán et al. (2018):
"Making the assumption that any change in the objective risk of flooding ceteris paribus results in an equal change in the subjective risk of flooding we thus identify the relationship between the house price discount and the subjective risk of flooding from the inter-study variation in the objective risk of flooding." (p. 675, Ecological Economics).

The meta-regression utilizes a random effects model with weights inversely related to the error variance. In this case, the meta-regression does not allow for an alternative weighting scheme. Different methods are proposed for estimating the between-study variability. Restricted maximum likelihood (REML) is the default estimation method because it performs well in most scenarios (StataCorp, 2023). This method is also used in this meta-regression.

Studies in coastal flood-prone areas are subject to significant publication bias and produce estimates indicating a price premium. Including both coastal and inland studies in the regression might jeopardize the internal validity of the estimates and is thus problematic (Beltrán et al., 2018). To examine this, the regression is conducted both with and without coastal estimates. When the coastal estimates are included, the model exhibits a substantially lower R-squared, which measures the goodness of fit, than when they are excluded. Next to that, the coefficient on (*Flood risk*), the variable of interest, is positive and insignificant, contrary to the expected sign. Consequently, coastal estimates, reported in studies 6, 11, and 13, have been omitted from the final regressions. The regression that incorporates coastal estimates can be found in the appendix.

In the literature, various functional forms are frequently employed to examine the decay of flood risk discount over time (Atreya & Ferreira, 2015; Atreya et al., 2013; Bin & Landry, 2013). These include a linear specification, a logarithmic transformation, a ratio specification, and a square root specification. Beltrán et al. (2018) find that the ratio transformation is the preferred transformation for the variable (*months*) in their regression based on the goodness-of-fit criterion. This study also tests the various functional forms, and the results confirm the preference for the ratio transformation in the regression analyses. Therefore, a linear functional form and the ratio functional form are included in the meta-regressions. In Model (1), a linear function is employed, expressed as $f(months) = months$, in Model (2), the ratio function is defined as $f(months) = (months - 1) / months$.

To further assess robustness, regressions are initially conducted without study fixed effects and subsequently with study fixed effects. The introduction of dummies for individual studies helps account for unobserved heterogeneity at the study level, which is particularly important given the diverse regions in which the studies are conducted. The study from Atreya & Ferreira (2015) serves as the reference study in this regression. Conducted in Georgia, U.S., it explores the impact of tropical storm Alberto on house prices. This study reports the highest flood risk discount in the meta-sample, simplifying the interpretation of the meta-regression.

4. RESULTS & DISCUSSION

4.1. Subsample meta-analysis and meta-regression results

Table 3 provides the random-effects model statistics for the combined effect sizes of different subsamples. For each subsample, the number of estimates, the summary statistic with the 95% confidence interval, tau^2, the Q-statistic, and I^2 are reported. In Table 3, weights for each estimate are calculated using the inverse-variance estimation method, while in Table 4, weights are calculated based on sample size. The two models show consistent signs for the effect sizes, with small variations in magnitudes and occasional differences in significance level. The highly significant Q-statistic and high percentage of I2 indicate significant heterogeneity in effect sizes. This emphasizes the suitability of using the random effects model to address the observed variability in the data.

TABLE 3: Meta-analysis: Summary statistics for RE model with inverse variance weights

Coast	**N**	**Summary statistic**	**95% conf. Interval**	**tau^2**	**Q-stat**	**I^2 (%)**
All	191	-0.034***	[-0.050; -0.018]	0.0104	3193.48***	99.25
100-year floodplain	166	-0.035***	[-0.054; -0.017]	0.0120	3014.52***	99.35
500-year floodplain	25	-0.015*	[-0.031; 0.001]	0.0010	164.18***	90.70
Inland	153	-0.052***	[-0.062; -0.041]	0.0027	1344.05***	97.51
Inland 100-year	132	-0.056***	[-0.068; -0.044]	0.0031	1182.89***	97.86
Inland 500-year	21	-0.026***	[-0.045; -0.007]	0.0010	125.33***	89.80
DID Inland Pre	42	-0.045***	[-0.059; -0.031]	0.0012	564.99***	95.65
DID Inland Post	72	-0.089***	[-0.113; -0.065]	0.0067	253.21***	82.30
Coast	38	0.071***	[0.024; 0.118]	0.0203	1845.43***	99.16
DID Coast Pre	12	0.037	[-0.028; 0.102]	0.0112	71.81***	98.78
DID Coast Post	6	-0.065***	[-0.082; -0.049]	0.0000	1.11	0.00

Notes: *, ** and *** implies rejection of H0 at the 10%, 5%, and 1% significance level

TABLE 4: Meta-analysis: Summary statistics for RE model with sample size weights

Coast	**N**	**Summary statistic**	**95% conf. Interval**	**tau^2**	**Q-stat**	**I^2 (%)**
All	191	-0.045***	[-0.073; -0.017]	0.0104	3193.48***	99.25
100-year floodplain	166	-0.025*	[-0.053; -0.004]	0.0120	3014.52***	99.35
500-year floodplain	25	-0.106***	[-0.157; -0.055]	0.0010	164.18***	90.70
Inland	153	-0.078***	[-0.101; -0.055]	0.0027	1344.05***	97.51
Inland 100-year	132	-0.062***	[-0.084; -0.040]	0.0031	1182.89***	97.86
Inland 500-year	21	-0.119***	[-0.175; -0.063]	0.0010	125.33***	89.80
DID Inland Pre	42	-0.064***	[-0.094; -0.034]	0.0012	564.99***	95.65
DID Inland Post	72	-0.104***	[-0.160; -0.047]	0.0067	253.21***	82.30
Coast	38	0.092***	[0.044; 0.139]	0.0203	1845.43***	99.16
DID Coast Pre	12	0.071**	[0.003; 0.140]	0.0112	71.81***	98.78
DID Coast Post	6	-0.067***	[-0.085; -0.049]	0.0000	1.11	0.00

Notes: *, ** and *** implies rejection of H0 at the 10%, 5%, and 1% significance level

The overall effect size indicates a discount of -3.4% for all houses in floodplains. When examining properties located in inland floodplains, this discount is larger at -5.2%. For coastal properties, the effect size is +7.1%. As mentioned earlier, this is most likely the result of not adequately controlling for amenities associated with proximity to the coast (Bin & Kruse, 2006). According to Beltrán et al. (2018), it is currently impossible to draw reliable conclusions from studies conducted in coastal regions.

When comparing the 100-year floodplain to the 500-year floodplain, the 100-year floodplain is expected to have a higher discount due to the higher expected flood damages. Notably, this expectation holds true in the meta-analysis model with inverse variance weights, but it does not align with the effect sizes observed in the model using sample size weights. This is likely a consequence of some relatively large effect sizes for the 500-year floodplain, accompanied by high standard errors. In the first model, the weight assigned to these estimates is small. However, in the second model, the information on standard errors is disregarded, resulting in larger weights being attached to them.

The summary statistics indicate a significantly greater discount for floodplain houses post-flood compared to pre-flood. This pattern holds true for both inland and coastal properties. More precisely, the effect size of -8.9% indicates that the discount for inland floodplain houses after a flood event is roughly double the discount observed before a flood event, which stands at -4.5%. The decrease in property values following a flood event is consistent with the literature. Morgan (2007) discovered that Hurricane Ivan increased flood risk perceptions and expected flood losses. Bin & Polasky (2004) similarly observe a significant difference in the discount between pre-flood and post-flood sales, where the post-flood discount is more than twice the pre-flood discount. Recent exposure to flooding heightens the perceived risks and costs linked to such events. Conversely, a lack of experience with flooding tends to mitigate these perceptions (Bin & Landry, 2013).

Table 5 displays the outcomes of the meta-regression, both with and without study fixed effects, incorporating both functional forms of the variable (*months*). Initially, the results of the model without study fixed effects will be discussed, followed by an examination of the model with study fixed effects as a robustness check.

TABLE 5: Meta-regression results

Variables	Without study FE (1)	Without study FE (2)	With study FE (1)	With study FE (2)
Flood risk perception				
$f\ (months)$	-0.000056	0.9823***	0.000044	0.9674***
	(0.00004)	(0.172)	(0.00004)	(0.148)
Flood risk				
Flood Risk	-4.2348***	-3.8696***	-4.7589***	-4.7133***
	(1.458)	(1.274)	(0.942)	(0.683)
Study context				
logfeet	0.0421***	0.0484***	0.0401***	0.0414***
	(0.014)	(0.011)	(0.013)	(0.010)
logprice	0.0439***	0.0288***	0.0529	0.0472*
	(0.014)	(0.010)	(0.033)	(0.025)
flooded	-0.2917***	-0.3079***	-0.2036***	-0.2241***
	(0.050)	(0.049)	(0.051)	(0.050)
scnd_flood	-0.0464**	-0.0050	-0.0478**	-0.0127
	(0.022)	(0.022)	(0.020)	(0.019)
near_miss	0.0890***	0.0785***	0.0959***	0.0793***
	(0.031)	(0.029)	(0.028)	(0.025)
dd_after	-0.0111	0.0395***	0.0165*	0.0473***
	(0.012)	(0.011)	(0.001)	(0.008)
Control variables of study				
amenities	0.0254*	0.0241*	-0.0161	-0.0215***
	(0.014)	(0.013)	(0.015)	(0.008)
real_p	-0.0022	0.0027	0.0110	-0.0014
	(0.013)	(0.011)	(0.015)	(0.010)
time_fe	-0.0061	0.0007	-0.0008	-0.0002
	(0.016)	(0.014)	(0.013)	(0.007)
Model characteristics				
spatial	0.0012	0.0061	-0.0004	-0.0002
	(0.008)	(0.007)	(0.005)	(0.002)
dd_hpm	-0.0042	-0.0060	-0.0106	0.0018
	(0.011)	(0.009)	(0.013)	(0.010)
Study characteristics				
med_sampleyear	-0.0049***	-0.0059***	-0.0192**	-0.0172***
	(0.002)	(0.001)	(0.007)	(0.006)
time_span	-0.0006	-0.0030**	-0.0015	-0.0016
	(0.001)	(0.001)	(0.002)	(0.001)
Study				
2			0.2582***	0.2494***
			(0.057)	(0.044)
3			0.3267***	0.3137***
			(0.060)	(0.047)
4			0.2676***	0.2798***
			(0.056)	(0.047)
5			0.3789***	0.3419***
			(0.080)	(0.068)
7			0.3881***	0.3636***

			(0.085)	(0.070)
8			0.3824***	0.3505***
			(0.088)	(0.072)
9			0.4061***	0.3859***
			(0.092)	(0.074)
10			0.2978***	0.2759***
			(0.078)	(0.068)
12			0.3401***	0.3138***
			(0.087)	(0.071)
14			0.3043***	0.2685***
			(0.107)	(0.091)
Constant	9.0803***	10.1539***	36.3802***	32.4827***
	(3.271)	(2.837)	(10.616)	(10.916)
Observations	153	153	153	153
R-squared	74.66	82.38	95.21	99.49

Note: REML Random-effects meta-regression. Dependent variable is Effect size. Standard error in parentheses. *** , **, * indicating significance at 1%, 5% and 10%, respectively.
Reference study = 1 (Atreya & Ferreira, 2015).

The discount for properties in a floodplain is greatest immediately after a flood and decreases over time, ultimately disappearing after about 5 years (Atreya et al. 2013; Bin & Landry, 2013). Interestingly, in model (1), where $f(months)$, the number of months since the last flood, is linearly specified, the variable is not statistically significant. This can be attributed to the linear specification assuming a constant effect for each unit increase in months, covering a wide range from 6 to 852. Consequently, it fails to capture the pattern of rapidly decaying discounts that vanish after a few years. In model (2), where $f(months) = (months - 1) \ / \ months$, the variable is positive and highly significant. The ratio specification of the variable is a method of modeling a rapidly diminishing return to increases in months. This specification captures the pattern of house price recovery more effectively, as the marginal effect of each additional month becomes smaller. The higher R-squared indicates a better goodness of fit with this specification, aligning with the findings of Beltrán et al. (2018). The positive coefficient for $f \ (months)$ indicates that the price discount is greatest shortly after a flood and then diminishes over time.

The variable (*Flood Risk*) is of primary interest; it is statistically significant and negative, as anticipated. This reveals that the price difference for houses in a 100-year floodplain is -3.9% compared to houses outside the floodplain. This aligns closely with the estimate found in Beltrán et al. (2018), which is -4.6%.

The variables (*logfeet*) and (*logprice*) exhibit a significant positive impact on the effect size. This implies that when the square footage and sale price of a house increase, the negative impact of floodplain location on house prices decreases. In the study conducted by Lee (2015), the influence of floodplains on housing prices is investigated using a housing submarket framework characterized by median house sale prices. The findings reveal that the impact of floodplain locations on housing prices is the most negative in the low-income submarket and positive in the high-income submarket. One explanation for this is that the recovery pattern of house prices after a flood in the low-income submarket is slower than in the other submarkets, which is reflected in long-term house prices (Zhang & Peacock 2005, cited by Lee 2015, p. 246). The positive capitalization in the high-income submarket is likely caused by floodplain amenities, such as scenic views. Positive amenities are more prevalent in the high-income submarket (Lee, 2015). Additionally, Rajapaksa et al. (2017) point out differences in the valuation of environmental amenities and disamenities among various income groups.

Both the variables (*flooded*) and (*near_miss*) exert a significant impact on the effect size. As expected, properties that experienced flooding exhibit a more considerable discount, while properties in floodplains that were not flooded show a decreased discount, all else being equal. Atreya and Ferreira (2015) discover that the price discount for inundated properties is substantially greater than for comparable floodplain properties that were not inundated during a flood. The difference in discount is due to potential uninsurable flood damages as well as psychological costs and suggests that homeowners respond better to what they have visualized (Atreya & Ferreira, 2015). These outcomes are consistent with the principles of the Availability Heuristic (Atreya & Ferreira 2015; Hennighausen & Suter 2020; Kousky & Shabman 2015). The Availability Heuristic implies that in evaluating flood risks, individuals are inclined to shape their perceptions based on the ease with which they can bring relevant examples to mind. The perception of risk is influenced by both the time that has passed since the flood and the severity of the flood (Kousky & Shahman, 2015).

The coefficient on the variable (*med_sampleyear*) is negative and highly significant. This suggests that, all else being equal, the discount for houses in floodplains tends to be greater for transactions that occur in later years. One possible explanation for this is a shift over time in public awareness regarding climate change and its potential consequences, given that the literature associates flood zone price discounts with risk awareness (Belanger et al., 2020).

4.2. Robustness check

In the meta-regression that accounts for study fixed effects, all coefficients associated with individual studies are positive and highly significant. This implies the existence of systematic differences among the studies, which are captured by these dummy variables. The R-squared of 99.49 in this model indicates almost all variability in the dependent variable is explained by the independent variables in the model and therefore strengthens the robustness of the findings. Comparing this the model that does not incorporate study fixed effects, most variables exhibited consistent signs and significance, with slight adjustments in magnitude. The difference in house prices between floodplain and nonfloodplain areas is approximately -4.7%, which does not differ much from the estimate found in the model without fixed effects. The other main variable of interest, $f\ (months)$, retains high statistical significance, with a coefficient closely matching the one in the model without study fixed effects.

4.3. Discussion

This study finds different estimates for location in a floodplain. In the subsample meta-analysis, effect sizes are specified for inland and coastal floodplain properties, properties within 100- and 500-year floodplain levels, and properties sold before and after flooding events. Given the limitations to draw conclusions from coastal studies (Beltrán et al., 2018) and the widespread focus on 100-year floodplains, the effect size for "Inland 100-year" seems to be the most reliable and representative estimate within the subsample meta-analysis. The effect size suggests a price difference of -5.6% based on 132 observations for houses located in a floodplain compared to those outside the floodplain.

The meta-regression reveals effect sizes for four distinct models. The variation across these models stems from the inclusion of either a linear or a ratio specification for the variable (*months*), addressing the time elapsed since the last major flood. Another difference lies in whether study fixed effects are included or excluded. Based on the goodness of fit, the preferred model incorporates study fixed effects and adopts the ratio specification for $f\ (months)$. The model identifies a price difference of -4.7% for houses situated in a floodplain, specifically focusing on inland flooding within the 100-year floodplain. This particular estimate is favored over the one found in the subsample meta-analysis. This preference is attributed to the meta-regression's consideration of the short-term impact from recent floods (Beltrán et al., 2018).

The results of this meta-analysis are compared with those from prior meta-analyses on the topic conducted by Daniel et al. (2009) and Beltrán et al. (2018). Daniel et al. (2009) find a price difference of -0.6% for location within a 100-year floodplain, while Beltrán et al. (2018) find a price difference of -4.6%. Beltrán et al. (2018) state that the estimate of -0.6 is too small and very different from their estimate. The reason for this is that Daniel et al. (2009) incorporate observations from coastal and inland studies in their meta-regression. The estimate derived from the preferred model in this study; -4.7%, closely aligns with the one reported by Beltrán et al. (2018). Moreover, the 95% confidence interval of [-6.05, -3.37] for our estimate overlaps with the 95% confidence interval of [-5.81, -3.34] found for the preferred estimate in Beltrán et al. (2018). Therefore, it can be concluded that there is no significant difference in the estimates. This supports the hypothesis that the discount found is around the same order of magnitude as observed in the previous meta-analysis. Furthermore, Beltrán et al. (2018) report a similarly significant coefficient for the ratio-transformed variable (*months*). In their model, the coefficient for (*flooded*) is also negative, but it is not significant. One potential explanation is that they possess fewer inundation estimates in their meta-sample, possibly because recent studies more frequently incorporate inundation data in contrast to earlier ones.

Similar to all statistical tools, meta-analysis comes with its own set of limitations. Stanley (2001) discusses potential limitations of meta-analysis. First, there may be disagreement about which moderator variables should be included in the analysis. The moderator variables included in this analysis are drawn from Beltrán et al. (2018), the most recent meta-analysis on this subject. Notably, these moderator variables differ slightly from those listed in the meta-analysis conducted by Daniel et al. (2009). However, using the same dataset, both models produce similar estimates. Second, there is the possibility of giving excessive weight to the results of studies that present a large number of estimates. To address this concern, an alternative weighting scheme is incorporated alongside the standard method within the subsample meta-analysis. This introduces some variations in the magnitudes of effect sizes, but the overall interpretation remains largely unchanged. The incorporation of the alternative weighting in the meta-regression is not feasible with the Stata software. Consequently, only the standard weighting method is applied, with the expectation that this limitation does not significantly alter the overall interpretation of the model. Third, publication bias can be an issue in meta-analysis. Publication bias results from selective sampling, there are two main types of this bias (Beltrán et al. (2018). One type is directional, characterized by selection favoring a particular effect, for example, negative or positive. The other is statistical significance, where the selection favors results that are statistically significant. In this study, a funnel plot is employed to visually examine publication bias. Alongside this, a regression asymmetry test is conducted, revealing evidence of publication bias. Daniel et al. (2009) propose that in this context, although publication bias may not be entirely absent, it could be confused with observable and unobserved heterogeneity among the effect sizes, which is caused by differences between studies. Beltrán et al. (2018) discovered publication bias in studies focused on coastal locations but not in those addressing inland flooding. Hence, the exclusion of coastal studies from their analysis is replicated in this study as well. Fourth, meta-analysis faces criticism for its tendency to incorporate all empirical studies without regard for their quality. The quality of the primary studies in this research is likely not an issue, given that all studies are drawn from peer-reviewed journals.

In this study, the Boolean search strategy employed by Beltrán et al. (2018) is adopted to retrieve relevant studies from standard databases. According to Havránek et al. (2020), it is recommended that this step involves the collaboration of two or more researchers who should report a measure of their agreement for the relevant literature. However, this was not feasible for this study. This in combination with the limited available time for searching and reviewing literature may have led to the omission of some relevant studies in this analysis.

To ensure accuracy in this process of calculating effect sizes, initial effect sizes have been calculated for the studies within the meta-sample of Beltrán et al. (2018), and a comparison has been made to verify the consistency of the obtained estimates. The same estimates were successfully retrieved for most studies. However, in some studies, models with a spatial lag are employed. Beltrán et al. (2018) calculate the total effect for spatial log models following the approach outlined by Golgher and Voss (2016). This added complexity to the calculation, which is why only the direct effect is included in this study. According to Beltrán et al. (2018), the study outcomes remain largely unaffected, irrespective of whether the total or direct effect is considered.

5. CONCLUSION

This paper studies the variation in findings within the literature on the effect of flood risk on housing prices through a meta-analysis. Previous meta-analyses on the influence of flood risk on house prices, conducted by Daniel et al. (2009) and Beltrán et al. (2018), include studies up until 2013. The growing awareness of climate change and its associated impacts underscore the need for a renewed meta-analysis that incorporates more recent studies, providing valuable insights into the evolving dynamics of the housing market and the influence of environmental factors. The aim of this study is to explain variation in estimates found in the literature and to determine the overall effect of flood risk on house prices.

The meta-sample in this study comprises a total of 191 estimates obtained from 14 papers published after 2013. The price differences for houses located within floodplains, as indicated by these studies, exhibit substantial variation, ranging from a discount of 84% to a premium of 41.4%. On average, 2 out of the 14 studies identify a premium, while the rest of the sample indicates a discount. Subsample meta-analysis indicate a premium of 7.1% for houses in coastal floodplains. Significant differences are also found when comparing pre-flood estimates with post-flood estimates. The discount of 4.5% before a flood increases to 8.9% after the occurrence of a flood.

A meta-regression analysis is performed to determine the most accurate estimate of the overall impact of flood risk on house prices. In the meta-regression, the favored model reveals a -4.7% price differential for properties situated in an inland 100-year floodplain. The meta-regression is executed with two distinct specifications for the variable representing the time elapsed since the most recent flood. This is done to evaluate which specification more effectively captures the diminishing impact of the flood risk discount following a flood event. Furthermore, the model is run both with and without the inclusion of study fixed effects to address unobserved study heterogeneity. The four models consistently indicate a significant price differential ranging from -3.9% to -4.8%.

This study has its limitations. Firstly, only 2 out of the 14 studies in the meta-sample were conducted outside the United States. This is because the designation of flood zones, indicating the probability, originates from the United States and is not universally adopted. To enhance cross-regional comparisons, alternative methods for assessing flood risk should be considered. Second, Beltrán et al. (2018) assert that studies contributing multiple estimates result in the overrepresentation of specific studies. An alternative weighting scheme to address this overrepresentation was not feasible in the meta-regression. Exploring the impact of such an alternative weighting on the results could be of interest.

The results of this study contribute valuable insights into the relationship between flood risk and its impact on the willingness to pay among homebuyers. The capitalization of flood risk into property prices is influenced by individuals' subjective assessments, posing significant economic risks. It is therefore of great importance to increase awareness of flood risk among people. By doing so, the housing market can more effectively incorporate flood risk, ultimately mitigating financial and economic risks.

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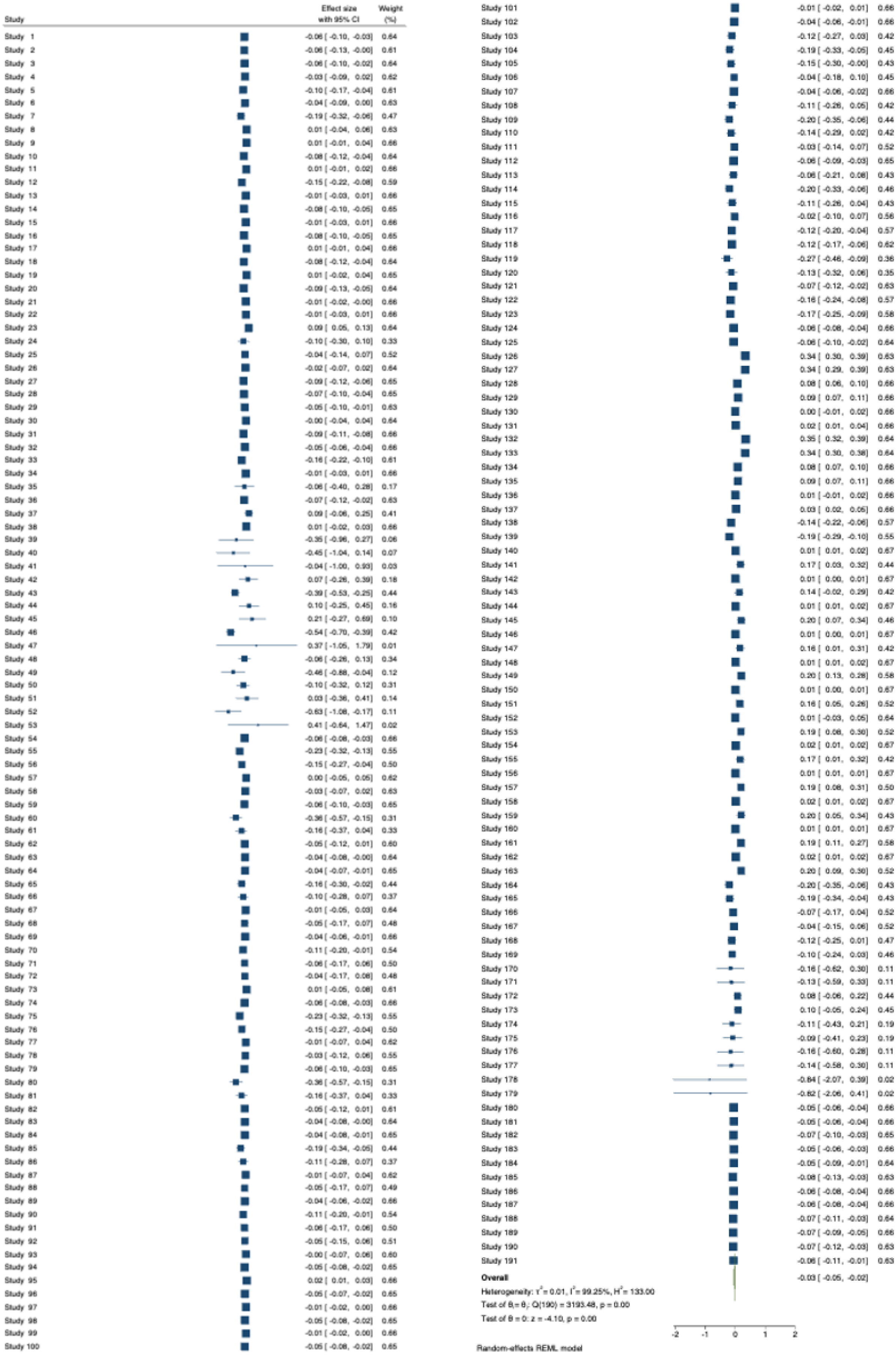
APPENDIX A: Forest plot



APPENDIX B: Regression table including coastal estimates

```
Random-effects meta-regression                    Number of obs  =       191
Method: REML                                      Residual heterogeneity:
                                                             tau2 = .005085
                                                           I2 (%) =   98.10
                                                               H2 =   52.50
                                                    R-squared (%) =   51.22
                                                  Wald chi2(16)   =  154.58
                                                  Prob > chi2     =  0.0000
```

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Months	-.0000225	.0000633	-0.35	0.723	-.0001466	.0001017
Floodrisk	4.133391	2.781117	1.49	0.137	-1.317499	9.58428
logfeet	.0345416	.0269033	1.28	0.199	-.0181879	.0872711
logprice	-.0013298	.0183651	-0.07	0.942	-.0373247	.0346651
flooded	-.147007	.0448638	-3.28	0.001	-.2349385	-.0590755
scnd_flooded	-.0880556	.0354373	-2.48	0.013	-.1575114	-.0185997
near_miss	.0382998	.0393204	0.97	0.330	-.0387668	.1153664
dd_after	-.0081415	.0234049	-0.35	0.728	-.0540144	.0377313
coast	.1110085	.0214822	5.17	0.000	.0689042	.1531128
amenities	.0046946	.0272827	0.17	0.863	-.0487786	.0581677
real_p	.0221213	.021396	1.03	0.301	-.019814	.0640566
time_fixed_eff~t	.0370114	.0321737	1.15	0.250	-.0260479	.1000706
spatial	.0030799	.0150257	0.20	0.838	-.0263699	.0325297
dd_hpm	-.0270187	.0194242	-1.39	0.164	-.0650893	.011052
med_sampleyear	-.0079846	.002804	-2.85	0.004	-.0134803	-.0024889
time_span	-.0093769	.0025459	-3.68	0.000	-.0143668	-.004387
_cons	15.78434	5.598713	2.82	0.005	4.811064	26.75762

Test of residual homogeneity: Q_res = chi2(174) = 1685.75Prob > Q_res = 0.0000