Does flood risk affect property prices? Evidence from a property-level flood score

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Abstract

One in six properties in England is exposed to flood risk and around half of those affected properties can be characterised as high risk. In this paper we examine whether the probability of flooding is capitalised in England's property market prices. We use a unique property-level data from Rightmove, UK's no.1 property website and the property-level $FloodScore^{TM}$ by Twinn by Royal HaskoningDHV. The latter metric estimates the likelihood of an individual property being flooded due to rainfall, overflowing rivers and tidal surges. We find that properties at risk are sold at 8.14% discount compared to non-affected properties and that the price discount reaches 32.2% for very high risk properties. By 2080 the flood events are expected to become more frequent and the average flood risk is projected to increase by 8%. Our empirical model suggests that one percentage point increase in properties' flood risk is associated with a decline of 0.07% to 0.11% in both sold and asking property prices. The impact is higher for properties of which flood risk is expected to increase or for regions that have recently experienced a flood event.

Keywords: *Climate change ; Flood Risk ; House Prices ; Flood Risk Discount; Flood Events*

JEL classification: *R3 ; O13 ; O18 ; Q54 ; Q56*

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1. Introduction

In 2015, the Paris Agreement coordinated a global response in the face of the imminent climate change threat. Countries agreed to adopt measures to limit global warming to well below 2 degrees Celsius by 2100, ideally aiming for an increase by 1.5 degrees Celsius or lower. According to Met Office data, since 1884 the annual mean air temperature in the UK increased by 13.4%[2] and in the coming century it is expected that the number of very hot days and the intensity and frequency of extreme precipitation events are very likely to rise further, resulting in more numerous natural disasters such as floods (Van Aalst 2006). Over the last 10 years in the UK, there were at least three severe flooding events; the 2013/14 South England winter flooding, the 2015/16 Northern Britain winter flooding and the 2019/2020 floods in Northern England, the Midlands and on both sides of the English/Welsh border. Global flood losses were estimated at $6 billion per year back in 2005 and they are projected to increase above $60 billion by 2050 in an optimistic scenario in which adaptation investments maintain sea-level rise and the probability of flooding (Hallegatte et al. 2013).

This paper investigates and quantifies the impact of flood risk on house prices. For our analysis, we use a large set of property-level data that includes more than 4.8 million observations for the period 2006-2022 which has been provided by Rightmove, the largest property website in the UK. For each property, we have data on its asking and sold price, qualitative characteristics available at the Rightmove website and a flood score provided by Twinn by Royal HaskoningDHV. Importantly, the dataset is unique and has never been used before in the literature. The property-level flood score is estimated using advanced flood modelling techniques and data from the Centre of Ecology & Hydrology and the Environment Agency. The metric provides us with a sophisticated and precise quantification of the likelihood of an individual property being flooded, due to rainfall, overflowing rivers and tidal surges, compared to more simple methods used in the literature, such as location within a floodplain or distance from a water body. In addition, it allows us to provide a country level analysis, and not to focus on a specific extreme weather event.

Economic theory and the majority of the empirical literature suggests that flood risk has a negative effect on property values. Flood events affect house prices via various channels such as the destruction of capital and increases in insurance costs (Carney 2015), but also indirectly due to change in consumption patterns (Giglio et al. 2021) and reduced economic activity (Indaco et al. 2021). In addition, extreme weather events result in unstable financial markets (IMF 2020) and consequently investments are significantly reduced since lenders become more cautious during a crisis (Hoffmann et al. 2013). Finally, such an event changes market dynamics and informed buyers could negotiate a lower since they have an advantage when the market is under distress after an extreme weather event (Piazzesi & Schneider 2009).

[2] The temperature is measured in degrees Celsius (°C).

However some empirical studies on flood risk and property prices have found mixed and conflicting results (Beltrán et al. 2018). Morgan (2007) finds that properties in coastal areas are sold at a premium as a result of the subsidized insurance premiums and the benefits of living close to the water (ocean view, water-based recreation opportunities) which outweigh the risks from a future flood event.[3] When Hurricane Ivan hit the Florida-Alabama coastline in 2004, it resulted in a significant market correction with property prices dropping by 15%. Pryce et al. (2011) provide a potential explanation. They argue that there is no adequate awareness of flood risk. Market participants are characterised by "*amnesia*" and "*myopia*" regarding the probability of a future flood event. Therefore, price discounts can be a result of a flood event, but not necessarily of flood risk (Lamond et al. 2010).

Our paper provides further empirical evidence to this debate. Firstly, our data suggests that there is on average a 8.14% flood risk discount on exposed properties compared to non-affected properties. Secondly, all properties, even the ones with a low (but not zero) probability of experiencing a flood in the future are sold at a discount. Low-risk properties are sold with a discount of 1.3% which can reach 32.2% for properties projected to face a flood event with almost certainty. Our empirical analysis shows that for a one percentage point increase in property's flood risk is associated with price discounts between 0.07% and 0.11%. The impact is significantly higher for properties of which flood risk is projected to increase between 2050 and 2080. Thirdly, our paper is one of very few studies that explore whether flood risk is capitalised in asking property prices. Our empirical analysis suggests that flood risk affects both the seller's asking and buyers offer prices, which could be attributed to expert services, such as Twinn or the Governmental Environmental Agency, reducing information asymmetries between sellers and buyers by quantifying a dwellings exposure to the risk of flooding.

In addition, we explore the asymmetries between flood risk and property prices. Firstly, we find that the effect is not homogeneous across time. More specifically, in periods after an extreme weather event occurs, buyers are more aware of flood risk and its impact on property prices is stronger. Secondly, property characteristics are not priced the same across the property price distribution. Higher-priced homes value certain characteristics, such as the number of bathrooms and property size, differently from buyers of lower-priced homes (Zietz et al. 2008). For that purpose, we employ a quantile regression approach that allows us to quantify the impact of flood risk across the distribution of property prices. Quantile regressions complement our benchmark model specification by identifying how differently property prices respond to flood risk at different quantiles (Mak et al. 2010). Our empirical findings show that the discount due to flood risk is larger for properties located in the left quantiles of the conditional distribution compared to less affordable properties, which indicates that lower-priced home buyers place a higher value on the risk of flooding.

[3] Similarly, Rajapaksa et al. (2017) and Beltrán et al. (2018) find that the relationship between environmental factors and property prices is not linear. Houses in close distance to a river have an additional amenity value that outweighs flood risks.

The rest of the paper is structured as follows. Section 2 reviews the literature. In Section 3 we describe the dataset and report summary statistics. Section 4 discusses the empirical methodology and results. In Section 5 we present the robustness tests results. Section 6 examines the asymmetries in the relationship between flood risk and property prices. Finally, Section 7 concludes.

2 Review of recent studies

Batten (2018) provides an empirical review of modelling techniques related to climate risk. She distinguishes between transition risk that is related to the transition to a low-carbon economy (Batten et al. 2016) and physical climate risk. The latter is defined as the risks arising from climate-related hazards (e.g. sea level rise, flooding, temperature changes, tornado activity) with the vulnerability of exposure of human and natural systems. For instance, temperature changes drive down economic activity via reduced investments, lower productivity and declines in industrial and agricultural production (Colacito et al. 2019, Acevedo et al. 2020). The literature finds a strong negative impact from climate change on real estate markets. The studies tend to focus on air pollution (Amini et al. 2022), earthquakes (Singh 2019), hurricanes (Hallstrom & Smith, 2005) and tornadoes (Donadelli et al. 2020). They all find a significant adverse effect on the exposed properties.

This paper contributes to the literature of flood risk and house prices. We present a country-level analysis for a very large number of properties over a prolonged time period, whereas most of the literature focuses on specific weather events in certain locations. For instance, Ortega & Taspinar (2018) investigate the effect of hurricane Sandy on the New York City housing market and found that damaged properties prices fell by around 10% more than non-affected properties. Similarly, the effect of Hurricane Flan and Hurricane Floyd in North Carolina resulted in a decline of 5.7% and 8.8% in house prices (Bin & Landry 2013) and the tropical storm Alberto in 1994 was followed by a temporary decline in property prices in Alabama, Georgia, and Florida. The impact varied between 28% to 47%, but the effect was found to be temporary (Atreya et al. 2013). More recently, Zhang (2016) and Zhang & Leonard (2019) study the effect of flood risk in the Fargo in North Dakota and Moorhead in Minnesota. Their empirical findings indicate that following a flood event house prices are discounted by 13% and that this discount exceeded 20% for properties within 1000 feet from the floodplain. All the aforementioned studies use a quasi-experimental design with a difference-in-differences approach. The main drawbacks of this approach is that all properties in the affected areas are treated as equal exposed and the analysis does not disentangles the effect of the occurrence of a flood and the actual damage caused from flooding in the treated group of properties (Atreya & Ferreira, 2015 ; Beltrán et al., 2019).

The distinguishing feature of our paper is the use of the unique Rightmove & Twinn dataset that allows us to quantify the objective level of flood risk that is specific to a particular house controlling for its characteristics. To incorporate flood risk into our analysis, we employ a hedonic price framework, which is a common method to examine the impact of a natural disaster. Previous examples such as Bin

& Polasky (2004) and Morgan (2007) use a similar hedonic property price function, but they do not attempt to explicitly quantify flood risk as it is only incorporated in the model as a dummy variable, depending on whether the property is inside or outside the floodplain. Our property-level flood risk also allows us to run a series of robustness tests excluding high risk and recently affected properties, as suggested by Hallstrom & Smith (2005), to account for the main drawback of the DiD approach.[4]

Of particular interest to this paper, Belanger & Bourdeau-Brien (2018) study the effect of flood risk on a smaller sample of around 600,000 English residential properties. Following the literature, they use dummy variables for properties that are built in a floodplain or near water to capture flood risk.[5] Their findings suggest that there is a significant flood risk discount in waterfront properties but that the impact is considerable also for dwellings further away from the water body. However, the floodplain dummy variable, similarly to the DiD approach, treats all properties the same (as high or zero risk) and ignores the fact that not all properties within a floodplain are not equally exposed.[6] Property's location within the floodplain is not necessarily the best indicator of flood risk since it does not take into consideration other important factors. McKenzie & Levendis (2010) study Hurricane Katrina, which was a standing-water flood and therefore property elevation was of primary importance. They argue that the likelihood of flood risks and the associated discounts are inversely related to the elevation of the property within the floodplain. In other words, the location within a floodplain captures the risk of flooding, but not necessarily the extent of flooding since properties are at different elevation levels, implying that the flood effect will not be homogeneous. Our technically advanced and more accurate flood risk metric differentiates this paper to the rest of the literature, since it provides a property-specific objective flood risk assessment across properties within and outside the floodplain.

Finally, this paper contributes to the literature examining how different quantiles of property prices in a distribution respond differently to shocks. We employ a quantile regression model that allows us to explore the differential effect of flood risk on lower and higher-priced houses. This methodological approach is commonly used to explore changes in the entire distribution of house prices (Zietz et al. 2008, Mak et al. 2010, McMillen 2008, 2015). McMillen (2008) applies a quantile hedonic house price function to examine the change in the distribution of house prices in Chicago between 1995 and 2005. His findings suggest that the house price distribution shifted farther to the right than the lower end or in other words, higher-priced homes being even more highly priced than before. Location and housing attributes, such as property types, cannot fully explain changes in the house price distributions.[7] A

[4] Beltrán et al. (2019) use a repeat-sales approach to overcome this issue, but this not possible in our dataset because the data includes a unique ID for each listing and not for each property.

[5] Rambaldi et al. (2013) examine the 2011 Brisbane flood in Australia. They measure flood risk as the vertical distances of house relative to a flood level that occurs on average once every 100 years and they find that properties are sold at a 5.5% discount for each metre below the defined flood level.

[6] Belanger & Bourdeau-Brien (2018) is one of the few studies that also include property elevation controls.

[7] Deng et al. (2012) present similar findings for the property market in Singapore during the two boom periods of 1996 and 2005–2007.

similar quantile approach has been adopted by Zhang & Yi (2017, 2018) in their study of the Beijing property market and how housing characteristics are valued differently across the property price distribution. We follow Zhang & Yi (2017) and we use the terms higher/lower-priced properties to denote the ones located in the lower and upper quantiles of the property price conditional distribution. Therefore a higher-priced property is more expensive compared to others with similar characteristics.

Our paper is one of the first that examines the heterogeneous effect of flood risk on the conditional distribution of house prices in England. One of the few studies in the literature, Zhang (2016), follows a similar approach for the Fargo-Moorhead Metropolitan Statistical Area between 2000 and 2013 but they measure flood risk based on the distance from a 100-year floodplain. Our data allow us to explore more deeply the asymmetric relationship between flood risk and property prices. More specifically, we examine the average discount from a one per centage point increase in flood risk across different percentiles of the property price distribution. The results indicate that the impact of flood risk is asymmetric across the conditional distribution of property prices and the effect is more significant for conditional lower-priced rather than higher-priced houses.

3 Data

3.1 Rightmove property prices data

We obtain data for 4.8 million listings in England from Rightmove. Our data includes the asking and sold price and date, number of bedrooms and the year the property was built. Our sample only includes single-family houses for the period 2006 up until August 2022.[8]

[Insert Tables 1 & 2]

Tables 1 and 2 display the property prices summary statistics per group and per year respectively. In total we have data for 4,882,880 individual listings at the Rightmove website of the average asking property price is £309,518. Of those listings two out of three[9] led to a sale. The average sold price is £277,264, which is as expected lower (-10.42%) than the asking price. Data is then divided into five main categories depending on their property type. One out of three properties are classified as detached, which is the most expensive category with an average sold price of £377,932. Semi-detached and terraced properties are priced at around £216,398 and £201,941 respectively. Bungalows are sold at £248,867 and finally 6-7% of our sample is unclassified. Our sample includes data from 9 English regions. The area around London (South East and Outer London) is most expensive with an average sold price of just above £350,000. East Anglia and South West are also priced higher than the rest of England at £286,011 and £279,533 respectively. The most affordable houses are in the Yorkshire and

[8] Due to budgetary limitations, we exclude properties in Inner London which are mainly apartments, Wales and Scotland. In addition, we do not have data on other property characteristics, since they are not available in the Rightmove website.

[9] The percentage refers to the entire sampling period 2006-2022.

East Midlands regions with an average price of around £200,000.[10] Table 2 displays the average asking and sold property pric e in each year. Our sample is balanced across all years. Since 2012, (nominal) property prices increased steadily by an average rate of 4%. Prices in 2019 were stagnant but the market bounced back, and prices increased by more than 7%.

3.2 Measuring flood risk

During the conveyancing process, house buyers in England receive a flood risk report informing them whether the dwelling is at risk of flooding in the future. They either continue with the transaction, withdraw from it or re-negotiate the price. In our study, we use Twinn $FloodScore^{TM}$ to quantify flood risk. The flood risk metric is assigned to every addressable property in Great Britain and Northern Ireland and considers risk from fluvial, pluvial and tidal sources. It uses advanced flood modelling techniques and incorporates the most current hydrology data from the Centre of Ecology & Hydrology, building stock data from Ordnance Survey, and the latest high resolution LiDAR from the Environment Agency. As we discussed previously, the other flood risk variables the literature uses are not always accurate due to property/regional characteristics, such as elevation and infrastructure.

[Insert Figure 1]

Figure 1 is provided by Twinn and illustrates how properties near a water body can have low exposure to flooding. The Figure shows that properties near the shore are not at risk of flooding, whereas properties located further away are considered to be more exposed. The main advantage of our metric is that it is a household-level flood risk measure as it estimates the likelihood of an individual property being flooded due to rainfall, overflowing rivers or tidal surges, and differentiates between the damage caused to different house types. The flood risk scores are regularly updated following UK flood events. We have four alternative indicators of flood risk based on different emissions scenarios (low/moderate and high level of emissions) and two epochs (2050 and 2080).

Table 3A displays the average sold property prices for different levels of flood risk. As expected, non-affected properties are priced higher than those of medium or high risk and their pricing is consistent across the four emission scenarios. For our benchmark model specification, we use the more optimistic 2050 low/moderate emissions scenario. Based on this scenario, 16.45% of all properties (803,057) in our sample are exposed to medium or high flood risk.[11] When we extend the horizon to 2080, the percentage of high risk properties increases by 3.03%. In addition, if we adopt a more pessimistic high emissions scenario, 8.19% more properties are classified as high risk over the next thirty years (epoch 2050). The percentage of non-affected properties is constant across different scenarios at 80%-85%.

[10] All the aforementioned prices are the average across the sampling period 2006-2022.
[11] If we only use sold property price the percentage is 16.52% or 528,033 properties.

[Insert Table 3]

The effect of flooding has a very localised impact and the average flood risk varies across regions. As displayed in Table 3C, the highest values are observed in East Anglia, Yorkshire and North West at 12.49%, 10.79% and 10.25% respectively. In those three regions 13%-18% of the properties (in our sample) are at risk. Houses in the West and East Midlands have lower than average flood risk scores, varying between 3.77% and 4.73%. Less 12% of the houses are at risk in these regions. Regarding property types, semi-detached and terraced houses are more are at risk of flooding since any temporary protection measures, such as blocking doors, windows, vents and pipes, will not be effective unless their neighbours also take similar steps.

3.3 Flood risk discount statistics

Table 3 shows that houses at risk to flooding are sold at a lower price. In this section we shed further light on its impact. Figure 2A presents the average house price for different levels of flood risk. We observe that prices do not vary considerably for low/medium levels of flood risk. More specifically, houses with a flood risk score below 60% are sold at a discount ranging between 2.6% and 4%.[12] However, this discount is significantly larger for houses in the high flood risk score ranges, 81%-90% and 91%-100%, at 15.5% and 30% respectively. Flooding affects house prices, but the impact is driven by properties heavily exposed to this (extreme) risk.[13]

[Insert Figure 2]

Figure 2B displays the house price distribution for zero or very high flood risk properties in a five-year period (2017-2021).[14] The difference between the two distributions is clear with riskier properties more skewed to the left. As illustrated in both Figures, the average sold price of very risky properties is below £190,000, whereas the average value for zero flood risk houses is £270,000. In addition, only 2.12% of zero risk properties are priced below £100,000 compared to 7.18% for properties with a flood score above 80%. On the other hand, the house price distribution of non-exposed houses has a fatter right tail since 13.5% have a value of above £500,000. The percentage for expensive risky properties is just below 5.5%.

[12] For properties with a flood score between 60% and 70%, the average sold price is even above the zero risk properties. However this can be attributed to the regional decomposition of the sample. In this group more expensive regions (East Anglia and South East) are over-represented, whereas more affordable regions (Midlands) are under-represented.

[13] Interestingly, most of the properties with a very high flood risk are located in South West (22%) and East Anglia (37%) where the average house price is above our sample's average. See Table 1.

[14] We calculate the distribution for the 5 years to exclude the 2008 global financial crisis. However the inclusion of all years will not significantly change the distributions' shape.

4 Empirical Analysis

4.1 Methodology

In this section we empirically examine the relationship between flood risk and property prices. We follow the literature and employ a logarithmic hedonic property price modelling technique that is based on the assumption that a good's pricing, in our case of a property, is driven by its characteristics.

The repeated cross-sectional regression model has the following specification:

$$logPrice_i = \alpha + \beta_1 Flood_i + \beta_2 X_i + year_i + month_i + postcode_i + prop.type_i + \varepsilon_i \quad (1)$$

where $logPrice_i$ is the logarithm of the (sold) price of property i and Flood is the probability that the specific property will be affected by a flood event. As mentioned before the risk metric is based on a scenario with low/moderate emissions and a 2050 horizon. We expect a negative relationship between property prices and flood risk that would mean that the probability of flooding will be capitalised and these at-risk properties will be sold at a discount compared to non-affected houses. X_i is matrix of property characteristics that includes the number of bedrooms in the house and the year built.[15] The two variables are available for the majority of listings in our sample and they allow us to control for size and quality of the property. We expect that modern larger properties (built more recently and with more bedrooms) will be priced higher than average.

Moreover, we have to take into consideration that property prices exhibit significant seasonality. Our data suggests that the average sold price is 3.55% higher in the beginning of the school year (September) than the sample average. The period between July-September is the quarter with the most sales (27.2% of the annual sales). On the other hand, only 6.6% of all transactions are completed in January and overall the first half of the year the market is not as busy as in the second half. For that purpose, we include year and month controls to account for changes in the economic environment and seasonality.

In addition, house prices vary a lot across the country, as displayed in Table 1. Properties in Outer London and South East regions are sold 70%-75% higher than those located in Yorkshire and East Midlands.[16] Therefore, we include area postcode controls to account for regional differences and amenities related to the location of each property. Similarly given that detached properties are, on average, 87% more expensive that terraced houses, we include four dummy variables to control for property type. Finally, we remove outliers from our sample. We do not include in the regression analysis properties below £10,000 and above £10,000,000. In addition, we remove properties with no beds and those will more than 10 beds.

[15] The age of the property enters the model as a categorical variable based on the decade built.

[16] The property price refers to the average sold price for all properties in those regions for the period 2006-2022. The spread would be even greater if we take into consideration London city centre properties.

4.2 Results

The regression results are presented in Table 4. Across all model specifications, flood risk has a strong negative relationship with property prices. That indicates that property market participants take into consideration the probability of a flood event in their pricing. For each one percentage point increase in the probability of flooding, properties are sold at a discount between 0.07 to 0.11. In other words, if a low-risk property experiences a flood event,[17] its price is expected to drop by 5.6% to 8.8%. The results are consistent when we introduce a series of control variables. All the models are estimated with robust standard errors and year and month control variables. All other variables have the expected signs. Additional rooms increase prices by 27% to 36%, whereas the more recently a house was built the higher is its property price.[18] In Models (2) and (3) we present the empirical findings for the empirical model specification with all the property characteristics controls, the addition of which does not affect our results.

[Insert Table 4]

Based on the data from Twinn, flood risk is projected to increase for 380,098 properties in our sample by 2080. In other words, 11.9% of all sold properties or 73.4% of all exposed properties. The average projected increase in flood risk of the exposed properties is estimated at 8.5%. In a more pessimistic scenario of high emissions, the average increase can be up to 20.5% or in other words the average property-level probability of flooding is estimated at 9.65%. In Table 4, Models (4) and (5) include a flood risk projection dummy variable that takes the value equal to one if the property flood risk is projected to increase between 2050 and 2080. The variable enters the model as an interactive term to capture if it changes the impact of flood risk on property prices. The estimated coefficient has a negative sign and therefore strengthens the impact of flood risk on property prices. Based on our empirical results, a one percentage point increase in flood risk is associated with a 0.06% price discount, however if the flood risk of the examined property increases in the future, the discount is almost 50% greater (0.09%).

4.3 Asking property price data

As mentioned before not all listings resulted in a sale. Furthermore, the transacted price reflects the agreed outcome between the buyer and seller. We next examine whether sellers take into consideration flood risk in asking prices. The average flood risk of sold properties is estimated at 8.01%, whereas unsold properties' flood risk is 8.63%. In addition, based on data for the entire sample period, zero exposure to flooding increases the probability of a property to get sold from 63.3%[19] to 65.6%.

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[17] Assuming that the property has no severe damages from the flood and its flood risk was in the range between 0% and 20% and then increased to 100%.

[18] Our sample includes properties built between 1970 and 2010 and therefore we do not include old historic houses that could be sold at a premium.

[19] The percentage refers to the number of sold properties to total properties with very high flood risk.

However, flood risk is not the main driver of the relatively low percentages of sales completion. The average asking price of unsold properties is around £350,000, which is 22.6% greater than the asking price of properties that were sold. In total 74.61% of all completed sales were sold at a discount and in only 11.48% was the sold price above the asking price. For the remaining 13.91% the buyer and seller's prices matched. Overall, the average discount from the initial asking price in a transaction was 3.6%.

Table 5 presents the results for asking property prices. The inclusion of all asking property prices provides a good robustness test since they indicate whether sellers incorporate their flood risk in pricing their properties. The empirical results show that property owners recognize that the probability of a flood event affects their house value and are willing to list their properties at a discount if they are at-risk. The flood risk discount is estimated between 0.07-0.11% per one percentage point increase in flood risk. The controls for year built and number of bedrooms are positively correlated with the property's asking price. In addition, the impact of flood risk is stronger for properties whose projected flooding exposure will increase in the future.

As we mentioned above, three out of four sales were completed at a discount from the asking price. Interestingly, the average flood risk of these properties was at 8.11%, higher than the average and above those properties sold at a premium. On the latter group, the average flood risk is estimated at 7.42%.

[Insert Table 5]

In Model (10), we focus on the properties that are sold at a discount from their initial asking price. We estimate the benchmark model, but we use the spread between asking and sold price as the dependent variable. Our results show that there is a positive association between flood risk and the price discount. This empirical finding suggests that between two identical properties (same number of bedrooms, year built, region and type) sold at the same time period, the one with higher flood risk will be sold at a greater discount from the initial asking price. Taken together, this result and our findings for asking prices reveal that both buyers and sellers attach a lower value to a house which is more heavily exposed to flood risk.

5 Robustness analysis

5.1 Flood Zones

In this section we present a series of robustness checks. Firstly, we use data from the Environment Agency on flood zones. Each property is matched to a flood zone level based on its postcode. Postcodes are treated as a single point in space, allowing for the postcode to be looked up and the flood risk determined for that point. The values are obtained by Open Flood Risk that combines the Environment Agency's Risk of Flooding from Rivers and Sea with English postcodes from Open Postcode Geo. Based on the probability of flooding, there are four flood zones; In Zones 1 and 2 are included properties with a chance of flooding less than 1%, in Zone 3 are properties with a flooding probability between

1% and 3.3% and finally in Zone 4 are the high risk properties with a chance of flooding of greater than 1 in 30. The vast majority of properties in our sample (93.15%) belong in Zone 2, followed by Zones 1 and 2 with (6.35%) and only 0.51% is at the high risk zone.[20] In Model (11) of Table 6, we run the benchmark regression model with property type and flood zone controls.[21] The inclusion of the Flood Zone does not affect our findings which are quantitatively similar as in Model (3) and fully support our expectations and earlier findings.

[Insert Table 6]

5.2 Alternative samples and the COVID-19 period

Hallstrom and Smith (2005) suggest that to obtain unbiased estimated in the DiD approach, the analysis should not include affected properties. Based on the final sample used across all our empirical analysis, 83.3% of properties have no exposure to flooding, whereas 2% has a flood score equal to 1. The latter group includes properties that have damaged in the recent past and they are highly likely to encounter flooding in the future. For robustness purposes in Models (12) and (13) we remove these two groups of properties. Despite the fact that the sample changes, the coefficient of flood risk is negative and statistically significant in line with our previous findings. In addition, we test whether the COVID-19 period affected the dynamics between flood risk and property prices. As we observe in Table 2, the first year of the COVID-19 period (2020) there were around 305,000 listings, but only 61% resulted in an actual transaction, which indicates that the pandemic put the market on hold for a few months. 15.9% of properties were sold in the COVID-19 period between 2020-2022H1. To control whether the pandemic affects our benchmark findings, we run the model excluding the last three years. The findings are displayed in Model (14). They indicate the same relationship between flood risk and property prices in the period before and after the pandemic. In Model (15) we include a COVID-19 dummy variable as an interaction term. The estimate of the coefficient is statistically insignificant indicating that the pandemic did not affect the relationship between flood risk and property prices.

5.3 Middle Layer Super Output Areas (MSOAs) controls

In addition, we employ group of explanatory variables contains statistics available at the MSOA level. Across the country, there are significant differences in the standards of living and opportunities for work between regions. For robustness purposes we estimate the benchmark model with MSOA controls instead of postcode controls[22]. We include data on the 2018 net annual household income before housing costs, the 2020 population estimates for each area and the average life expectancy for males

[20] Our sample is relatively small for properties located in North West England, a region with many properties that belong in the high risk zone.

[21] Properties located in the same postcode area are in also in the same Flood Zone, so we do not include postcode controls in Model (11).

[22] Belanger and Bourdeau-Brien (2018) use MSOA and LSOA controls instead of postcode controls in their empirical analysis.

and females. All data are provided by the Office for National Statistics (ONS). The results are displayed in Models (17) and (16) with and without property characteristics controls, respectively. In both cases the relationship between flood risk and property prices is negative and statistically significant in line with our previous findings. With regards to the MSOA variables, the annual income and life expectancy is positively associated with property prices, whereas the relationship between property prices and population is negative. All estimated coefficients are negative and statistically significant.

5.4 Low vs. High flood risk properties

As discussed before, the property price discount is considerably higher for properties characterised as high risk. To confirm this hypothesis empirically, in Model (18) we estimate the benchmark model, but isolate the impact for low and high flood risk properties. We follow Twinn's classifications and we define high risk properties as those with a flood risk above 60% and low risk as properties with a flood risk score above 0% but less than 40%. Our empirical findings indicate that a one percentage point increase in flood risk of high risk properties is associated with a decline in price above 0.05%. On the other hand, the impact for low risk properties is significantly weaker and estimated to be a 0.02% marginal decline in value per one percentage point increase in flood risk.

6 Asymmetric dynamics between flood risk and property prices

In this section we examine whether the relationship between flood risk and property price is homogeneous across time and the price distribution. More specifically, we aim to answer the following two questions: Do weather events alter market participants' understanding and behaviour towards flood risk? and are low and high-priced properties equally affected by the probability of a flood event?

6.1 Extreme Weather Events: Testing for myopia in the housing market

Our empirical findings suggest that market participants take into consideration flood risk in their decisions. However, the effect could be mitigated by buyers' irrational behaviour or incomplete information. Pryce et al. (2011) suggest that market participants exhibit "*myopia*" and "*amnesia*", implying that perceived risk could diverge considerably from actual risk. In this section, we test whether buyers alter their behaviour and value houses with a lower flood risk more after an extreme weather event. We focus on the recent six major hydrological events as defined by the National River Flow Archive and the UK Centre of Ecology & Hydrology:

- **The 2019-2020 flooding:** After a prolonged dry period (2016-2019), the UK experienced several severe flood events between June 2019 and February 2020. The most affected areas were North Wales, North England and the Midlands. The property damage was severe for areas such as Derbyshire and Lincolnshire with the estimated insurance pay-outs to be estimated at £110 million (Sefton et al. 2021).

• **The 2015-2016 flooding:** A series of heavy rainfalls resulted in flooding in the period between December 2015 and February 2016 in North West England. For the UK, December 2015 was the wettest month and it was the second wettest winter since 1910 (Barker et al. 2016).

• **The 2013-2014 flooding:** From December 2013 to February a succession of persistent rainfall and strong winds affected the UK. According to the Environmental Agency the damage was estimated at around £1.3 billion for England and Wales. The property damage alone was at £320 million since more than 10,000 houses were affected by a combination of coastal, pluvial, fluvial and groundwater flooding (Muchan et al. 2015). The effect was spread across the country and mostly South England.

• **The 2012 flooding:** Following a dry period between 2010 and early 2012, in spring of 2012 and on through the winter of 2013, there was extensive flooding across much of England. This was an extreme expression of the variability of UK climate. Flood alerts were widespread from South West England to Scotland.

• **The 2009 flooding:** The 2009 floods were primarily caused by heavy and persistent rainfall over an extended period of time, leading to rivers overflowing their banks and widespread waterlogging. One of the hardest-hit areas was North West, and most specifically, the Lake District in Cumbria. The floods caused extensive damage to infrastructure, disruption to the transportation network and a substantial economic impact, with businesses suffering due to property damage and closures.

• **The 2007 flooding:** During the summer of 2007, the UK suffered from a series of floods that affected various parts of the country. One of the worst-hit areas was the Yorkshire and Humberside region in northern England, but the floods caused damage to homes and businesses in other parts of the country such as the Herefordshire and Worcestershire in the Midlands and Gloucestershire and Oxfordshire in the South.

[Insert Figure 3]

Figure 3 displays the annual maximum observed flow (AMAX) measures in cubit meters per second as provided by the National River Flow Archive (NRFA). The original illustration is provided by Sefton et al. (2021) and allow us to depict the magnitude and spatial heterogeneity of flood events during our sample period. To incorporate this into our model, we construct an Extreme Weather Event (EWE) dummy variable that takes the value equal to one during periods a specific region experienced a flooding event, and zero otherwise. During our sample period, 150,222 properties were sold during and soon after an extreme weather event. These properties were sold a 18% discount (£224,851) compared to those non-affected (£265,523).

In Models (19) and (20) we add the EWE dummy variable as an interactive term that affects the impact of flood risk on property prices. The EWE variable captures the effect of perceived changes to flood risk. The difference between the two models is that in Model (20) we include the number of bedrooms, year built, property type. Both models include year and month controls. We do not include area postcode controls since our definition of an EWE affects all properties in the same region. According to our empirical findings, one percentage point increase in flood risk is associated with a 0.1% decline in the sold price but if the property is located in a region that an extreme weather event just occurred, the impact is estimated at -0.15%. To assess robustness, Models (21) and (22) assume that the impact of a weather event carries over the following quarter. The new EWE variable identifies 253,522 properties that were sold soon after (up to 3 months) a weather event. These properties are sold at a 6.3% discount compared to non-affected regions. The empirical findings suggest that the estimated coefficient of the interactive term is negative and statistically significant and confirms our previous results. Interestingly, the effect has weakened compared to the transactions that took place closer to the occurrence of the extreme weather event. Overall, the inclusion of the EWE variable has no effect on the estimated effect on objective risk but reveals that the discount due to perceived risk decreases as time after the event lengthens.

[Insert Table 7]

6.2 Who values flood risk more?

Standard linear regression models exhibit considerable limitations on studying distributional effects. In this section we examine the asymmetric effect of flood risk on different parts of house price-distribution. More specifically, we employ a quantile regression model to our hedonic price models. The model was introduced by Koenker & Bassett (1978) and captures the relationship between the property characteristics and different points in the conditional distribution of prices. The model explores the implicit pricing of housing characteristics for different percentiles across the distribution of property prices. The mathematical representation of the model is the following:

$$Y_i = X_i\beta_q + \varepsilon_{q,i} \quad (2)$$

Quantile regressions differ from the standard OLS approach since to obtain the estimate for beta, we minimize the sum of absolute not squared errors and it imposes different weights on the error term depending on the examined quartile. The quantile regression estimator (β) for quantile q minimizes the following objective function:

$$Q(\beta_q) = \sum_{i:y_i > z_i'\beta}^{N} q|y_i - x'_i\,\beta_q| + \sum_{i:y_i < z_i'\beta}^{N} (1-q)|y_i - x'_i\,\beta_q| \quad (3)$$

We estimate the model for more than one quantile simultaneously to allow for differences between quantile regression coefficients to be tested. The variance-covariance matrix is estimated by bootstrapping and 100 replications. The estimated coefficient described in the Equation (3) captures the marginal effect on the dependant variable conditional on the parameters of the explanatory variables estimated at the q-th percentile. The dependant variable is the logarithm of the (sold) property price and the matrix of explanatory variables includes flood risk, dwelling characteristics (the number of bedrooms and the year the property built) and monthly time controls as in the benchmark model.

[Insert Table 8]

Table 8 presents the quantile regression results for properties sold in 2021. Our findings suggest that the effect of flood risk is asymmetric and buyers of properties in lower quantiles of the conditional distribution value more flood risk compared to buyers of properties in the upper quantiles.In other words, buyers and sellers of lower-priced properties value more the costly implications of flooding. Contrarily, the impact of flood risk on house prices at the upper tails of the conditional property price distribution are quite similar. Based on our empirical results, the quantile regression coefficient varies from -0.13 for conditionally lower-priced properties, to -0.1 for middle priced properties and to -0.07 for those in the upper quartile of the conditional distribution. Our results are in line with Zhang (2016) who finds that among properties located within a 100-year floodplain, low-priced properties have a larger flood risk penalty than higher-priced properties. Figure 4 displays the quantile regression coefficients of flood risk estimated for each year separately between 2017 and 2021 to assess robustness. Within each decile, the estimated impacts appear to be robust across time and they confirm our previous empirical findings.

[Insert Figure 4]

7 Conclusions

This work fills a gap in the literature by examining how flood risk can directly affect the English residential real estate market and builds the foundations for a better understanding and quantification of climate-related risk in the property market. Our findings provide evidence of a flood risk price discount for houses exposed to flooding. The discount affects both sold and asking property prices and their spread. It is analogous with properties' level of exposure. In addition, our empirical model suggests that a one percentage point increase in a property's flood risk score is associated with a decline of 0.07% to 0.11% in both the sold and asking price. In a pessimistic scenario, the average property flood risk is projected to increase by 11.73% which could cause a 1-1.3% decline in property prices. The impact is significantly greater when the property's probability of flooding is projected to increase in the future. Moreover, we find evidence that market participants value flood risk more in periods soon after an extreme weather event. We then shed light on another aspect of the relationship between house prices and flood risk. We employ, as an alternative to the standard OLS regression model, a quantile regression model to quantify the implicit pricing of property characteristics across different quantiles of the conditional property price distribution. Our findings suggest that flood risk has a stronger effect on lower-priced than higher-priced properties. Both buyers and sellers of low-priced properties attach a higher value to having a low flood risk house compared to properties at the upper tail of the conditional price distribution. Our empirical findings highlight the benefits of flood mitigation and adaptation programmes that focus on low-income neighbourhoods.

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Tables & Figures

Table 1: Summary Statistics per property group

A. Property Type						
	Obs.	%	Asking Price	Obs.	%	Sold price
Detached	1,737,622	35.59%	£425,502	1,080,218	35.59%	£377,932
Semi-Detached	988,012	20.23%	£230,670	667,080	20.23%	£216,398
Terraced	1,117,052	22.88%	£755,107	755,107	22.88%	£201,941
Bungalow	713,836	14.62%	£489,167	489,167	14.62%	£248,867
Unclassified	326,358	6.68%	£203.911	203,911	6.68%	£290.149
Total	4,882,880	100%	£309,518	3,195,483	100%	£277,264

B. England Regions						
	Obs.	%	Asking Price	Obs.	%	Sold price
South West	833,492	17.07%	£315,362	546,282	17.10%	£279,533
South East	1,266,904	25.95%	£407,969	835,196	26.14%	£358,726
East Anglia	983,559	20.14%	£315,115	642,177	20.10%	£286,011
East Midlands	681,178	13.95%	£225,068	451,518	14.13%	£205,600
West Midlands	454,333	9.30%	£247,868	297,993	9.32%	£224,291
Yorkshire	595,675	12.20%	£218,988	379,419	11.87%	£200,404
North West	3,109	0.06%	£281,598	1,708	0.05%	£243,251
North East	15,619	0.32%	£280,542	9.581	0.30%	£247,340
Outer London	49,011	1.00%	£409,472	31,649	0.99%	£364,307
Total	4,882,880	100%	£309,518	3,195,483	100%	£277,264

Note: The table reports property price summary statistics for alternative property types and regions. Table A presents the number of observations and the average asking and sold price of all properties in our sample grouped by type of property. Similarly, Table B presents the same statistics for properties located in different regions. The data is provided by Rightmove and refers to the period 2006-2022. This data is being used for across all empirical models in this paper and we only include properties that flood risk scores are available.

Table 2: Summary statistics per annum

	Obs.	%	Asking Price	Obs.	%	Sold price
2006	377,111	7.72%	£243,510	159,324	4.99%	£212,616
2007	387,624	7.94%	£256,011	256,643	8.03%	£236,928
2008	296,250	6.07%	£262,581	142,714	4.47%	£263,135
2009	234,099	4.79%	£258,362	151,166	4.73%	£222,980
2010	281,282	5.76%	£266,406	156,191	4.89%	£243,513
2011	268,087	5.49%	£266,152	162,556	5.09%	£233,310
2012	239,487	4.90%	£276,444	155,481	4.87%	£235,594
2013	272,008	5.57%	£278,939	186,481	5.83%	£241,981
2014	283,144	5.80%	£293,359	218,096	6.83%	£255,437
2015	275,239	5.64%	£312,051	212,451	8.65%	£271,947
2016	301,994	6.18%	£334,691	223,024	6.98%	£289,814
2017	301,422	6.17%	£345,688	233,717	7.31%	£308,859
2018	299,267	6.13%	£349,613	225,414	7.05%	£314,746
2019	269,951	5.53%	£348,900	204,719	6.41%	£314,738
2020	304,656	6.24%	£369,892	186,081	5.82%	£337,104
2021	277,483	5.69%	£396,731	282,225	8.83%	£362,929
2022	213,416	4.37%	£441,353	39,470	1.24%	£378,442
Total	4,882,880	100%	£309,518	3,195,483	100%	£277,264

Note: The table reports the property type summary statistics per annum. On average takes more than six months for a transaction to be completed and for the period 2006-2019 only two out of three resulted in a sale. As a result, the asking price dataset is larger than the sold price dataset.

Table 3: Flood Score summary statistics

A. Flood Risk Groups				
Horizon:	2050		2080	
Emissions Scenarios:	Low/Moderate	High	Low/Moderate	High
Zero Risk	£280,970	£280,970	£280,976	£281,002
Medium Risk	£271,858	£271,971	£270,318	£268,294
High Risk	£241,612	£242,386	£245,606	£249,728

B. Property Type				
Horizon:	2050		2080	
Emissions Scenarios:	Low/Moderate	High	Low/Moderate	High
Detached	6.99%	7.20%	7.61%	8.50%
Semi-Detached	7.60%	7.87%	8.26%	9.21%
Terraced	9.00%	9.27%	9.85%	11.03%
Bungalow	9.35%	9.61%	9.89%	10.69%
Unclassified	7.87%	8.11%	8.60%	9.60%

C. England Regions				
Horizon:	2050		2080	
Emissions Scenarios:	Low/Moderate	High	Low/Moderate	High
South West	8.54%	8.73%	9.10%	9.53%
South East	6.76%	6.98%	7.62%	8.75%
East Anglia	11.88%	12.17%	12.67%	13.72%
West Midlands	3.79%	3.89%	4.26%	4.93%
East Midlands	4.74%	4.86%	5.25%	6.01%
Yorkshire	10.72%	11.00%	11.31%	12.40%
North West	10.50%	10.64%	11.04%	11.96%
North East	5.57%	5.70%	6.16%	7.08%
Outer London	8.13%	8.61%	8.92%	10.07%

Note: The table reports the Flood Score summary statistics. Twinn data provide four alternative scores for each property based on the horizon (2050 and 2080) and emissions level; optimistic (low/moderate emissions) and pessimistic (high emissions). Table A reports the average sold price for properties with zero, medium or high flood risk. Tables B and C present the average probability of a flood event for different property types and across different regions. The data refers to the period 2006-2022.

Table 4: Regression results

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Dependent Variable			Log Sold Property Price		
Flood Risk	-0.114***	-0.070***	-0.072***	-0.076***	-0.062***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FFR * Flood Risk				-0.022***	-0.027***
				(0.00)	(0.00)
Number of Bedrooms		0.309***	0.241***		0.241***
		(0.00)	(0.00)		(0.00)
Constant	11.367***	11.181***	11.367***	12.141***	11.367***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year Built	NO	YES	YES	NO	YES
Property type controls	NO	NO	YES	YES	YES
Area Postcode controls	YES	YES	YES	YES	YES
Year controls	YES	YES	YES	YES	YES
Month controls	YES	YES	YES	YES	YES
R^2	0.32	0.68	0.74	0.59	0.74
Observations	1,912,696	1,912,696	1,912,696	1,912,696	1,912,696

Note: The table reports the results of the regression model. The dependent variable is the sold property price. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5: Regression results | Asking Property Prices

	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)
Dependent Variable		Log Asking Property Price			Asking-Sold Price
Flood Risk	-0.115***	-0.071***	-0.074***	-0.063***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Future Flood Risk				-0.027***	
				(0.00)	
Number of Bedrooms		0.304***	0.237***	0.237***	-0.004***
		(0.00)	(0.00)	(0.00)	(0.00)
Constant	12.155***	11.167***	11.351***	11.351***	0.061***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year Built	NO	YES	YES	YES	YES
Property type controls	NO	NO	YES	YES	YES
Area Postcode controls	YES	YES	YES	YES	YES
Year controls	YES	YES	YES	YES	YES
Month controls	YES	YES	YES	YES	YES
R^2	0.34	0.68	0.75	0.75	0.01
Observations	1,912,696	1,912,696	1,912,696	1,912,696	224,792

Note: The table reports the results of the regression model. In Models (6) – (9), the dependent variable is the asking property price. In Model (10) the dependent variable is the difference between the logarithm of asking price and the logarithm of sold price. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6: Regression results | Robustness

	Model (11)	Model (12)	Model (13)	Model (14)	Model (15)	Model (16)	Model (17)	Model (18)
Description:	Flood Zone controls	Only At-risk properties	Remove properties with Flood Risk = 1	Exclude COVID-19 period	COVID-19 dummy variable	MSOA controls		Low vs. High risk
Flood Risk	-0.116***	-0.054***	-0.049***	-0.072***	-0.072***	-0.049***	-0.031***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
High Flood Risk								-0.050***
								(0.00)
Low Flood Risk								-0.021***
								(0.00)
COVID-19*Flood Risk					0.0002			
					(0.002)			
MSOA Annual Income						0.300***	0.021***	
						(0.00)	(0.00)	
MSOA Population						-0.001***	-0.003***	
						(0.000)	(0.00)	
MSOA Life Expectancy						0.196***	0.009***	
						(0.000)	(0.00)	
Constant	11.851***	11.365***	12.758***	11.365***	11.367***	9.589***	9.952***	11.359***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Flood Zone controls	YES	NO	NO	NO	NO	NO	NO	NO
Region controls	YES	NO	NO	NO	NO	NO	NO	NO
Property Characteristics	YES	YES	YES	YES	YES	NO	YES	YES
Property type controls	YES	YES	YES	YES	YES	NO	YES	YES
Area Postcode controls	NO	YES	YES	YES	YES	YES	YES	YES
Year controls	YES	YES	YES	YES	YES	YES	YES	YES
Month controls	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.65	0.75	0.75	0.74	0.74	0.40	0.78	0.75
Observations	1,912,696	319,456	1,875,913	1,691,939	1,912,696	1,912,696	1,912,696	319,456

Note: The table reports the results of the regression model. The dependent variable is the sold property price. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The MSOA series are provided by the Office for National Statistics (ONS). The annual income is expressed in thousands of £, the population in thousands of people and the average life expectancy of men and women.

Table 7: Regression results | Extreme Weather Events

	Model (19)	Model (20)	Model (21)	Model (22)
Dependent Variable	Log Sold Property Price			
Flood Risk	-0.146***	-0.104***	-0.148***	-0.105***
	(0.00)	(0.00)	(0.00)	(0.00)
Extreme Weather Event*Flood Risk	-0.056***	-0.055**		
	(0.01)	(0.01)		
Extreme Weather Event (t+3) *Flood Risk			-0.023***	-0.024***
			(0.00)	(0.00)
Constant	12.204***	11.413***	12.204***	11.413***
	(0.00)	(0.00)	(0.00)	(0.00)
Property Characteristics	NO	YES	NO	YES
Property type controls	NO	YES	NO	YES
Year controls	YES	YES	YES	YES
Month controls	YES	YES	YES	YES
R^2	0.09	0.48	0.09	0.48
Observations	1,912,696	1,912,696	1,912,696	1,912,696

Note: The table reports the results of the regression model. The dependent variable is the sold property price. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 8: Quantile regression results

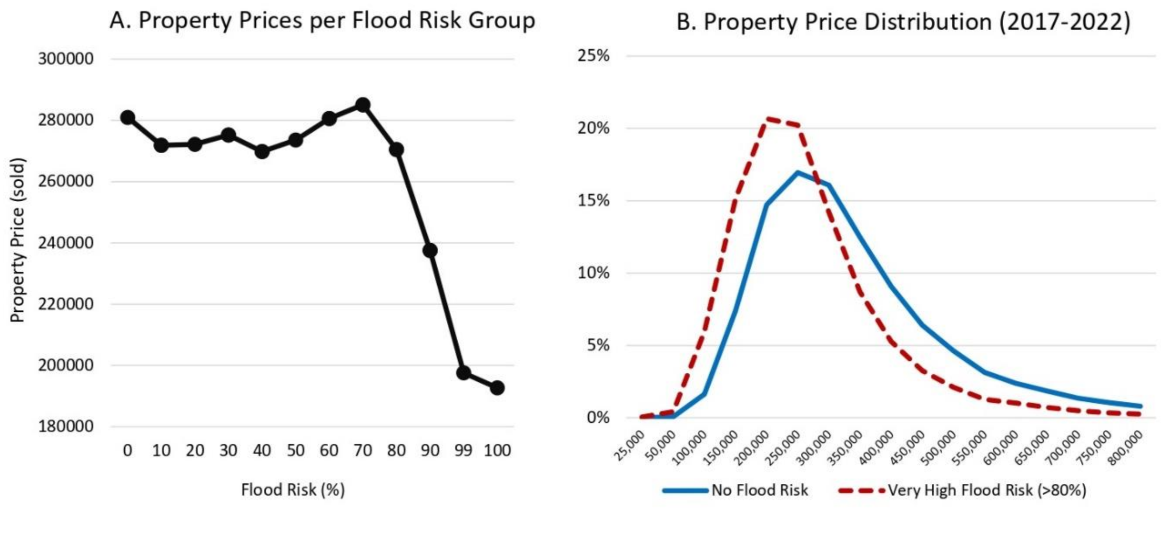
Dependent Variable:	Log Sold Property Price				
Quantiles:	0.10	0.25	0.50	0.75	0.90
Flood Risk	-0.131***	-0.124***	-0.100***	-0.080***	-0.070***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	11.401***	11.616***	11.852***	12.070***	12.228***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Property Characteristics	YES	YES	YES	YES	YES
Month controls	YES	YES	YES	YES	YES
R^2	0.23	0.23	0.24	0.26	0.28
Observations	87,767	87,767	87,767	87,767	87,767

Note: The table reports the results of the quantile regression model. The dependent variable is the sold property price. The sample period extends to properties sold between January 2021 and December 2021. Property characteristics include number of bedrooms, year built and the type of the property. Standard errors produced by bootstrapping with 100 replications and they are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Figure 1: Visualisation of Flood Risk estimation

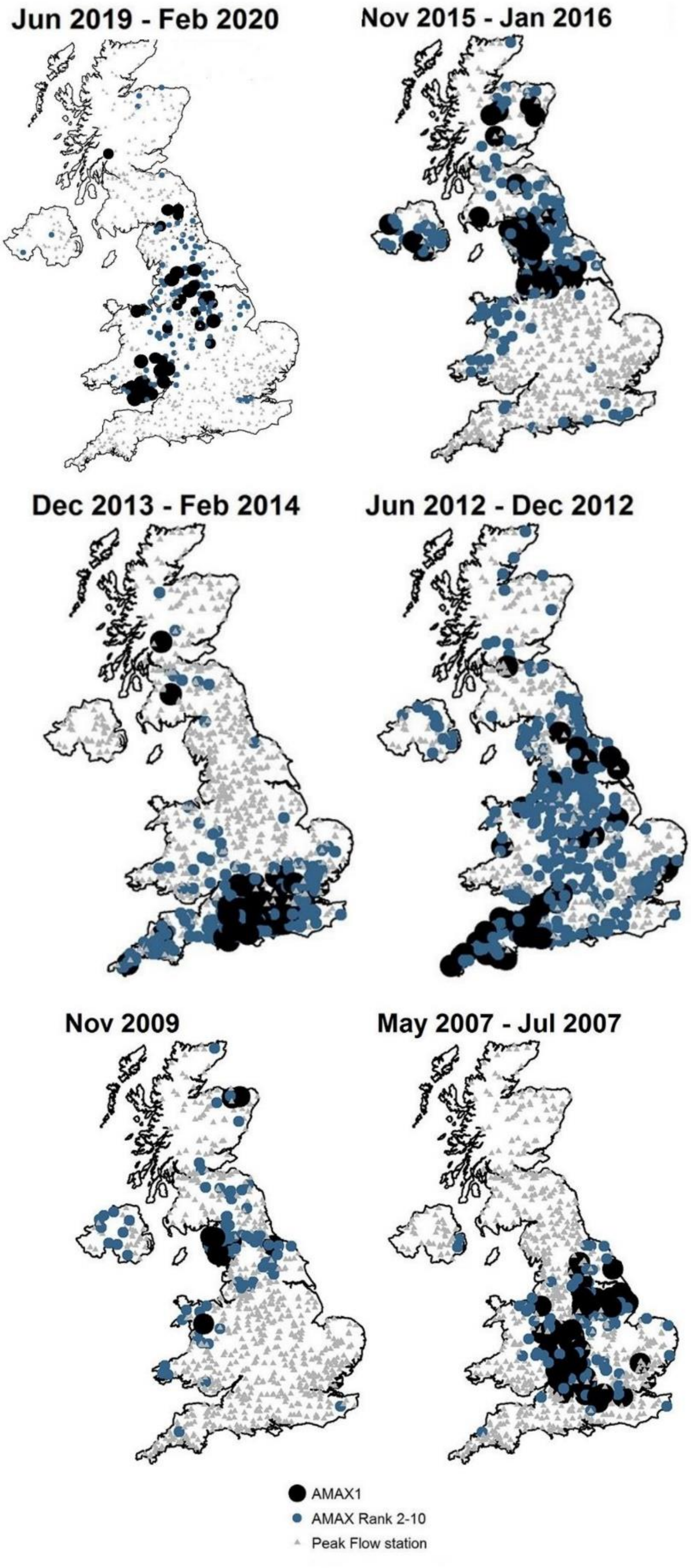
Note: The Figure illustrates how the Flood Score works for different properties. The visualisation shows that the distance from a water body is not the only criterion that affects the probability of a property being affected by a flood event. Source: Twinn.

Figure 2: Property prices and flood risk



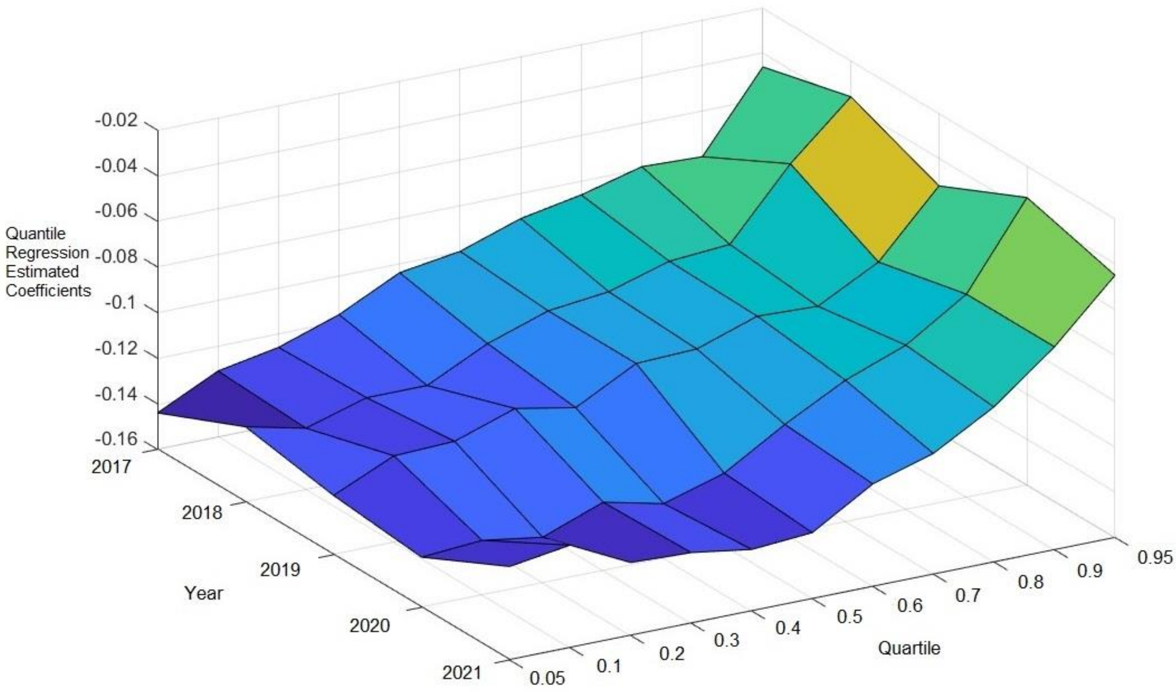
Note: Figure A displays the average (sold) property price for different levels of flood risk. To measure flood risk we use the more optimistic 2050 moderate emissions scenario as provided by Twinn. The data covers the period 2006-2021. Figure B plots the distribution of (sold) property prices for properties with zero (solid line) and very high (>80%, dotted line). The distribution is based on the five-year period 2017H2 to 2022H1.

Figure 3: Extreme Weather Events: Magnitude and Spatial Footprint



Note: The Figure shows the magnitude and spatial footprint of the six examined severe flood events occurred in the period 2006-2021. The small blue dots depict the largest observed flow (Annual Maximum or AMAX series) in each water year. The black dots stand for the AMAX1, the highest largest maximum observed flow in the AMAX series.
Source: Sefton et al. (2021) and the UK Centre for Ecology & Hydrology.

Figure 4: Quantile Regression Coefficients



Note: The Figure displays the estimated quantile regression coefficient of flood risk on property prices. The explanatory variables also include number of bedrooms and the year the property was built. The estimation was for each year separately between 2017 and 2021 and for quantiles between 5% and 95%. The estimation of the variance-covariance matrix is based on bootstrapping and 100 replications.