Climate Risks and House Prices: The Insurance Channel

Nicola Garbarino*, Benjamin Guin† and Jonathan Lee‡§

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Abstract

Can public policies addressing climate risks disrupt the housing market? In this paper, we study the effects of a UK flood reinsurance scheme in the property market. Leveraging a unique data set on the population of all property transactions in England, we document that this policy increases the value and transaction volume of flood-prone properties. The effects on property value are particularly strong in urban areas and areas with wealthier households. Our findings highlight the transition risk and wealth redistribution caused by the reinsurance scheme.

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*Ludwig Maximilian University of Munich & Ifo Institute for Economic Research. Email: Garbarino@ifo.de

†Bank of England. Email: Benjamin.Guin@bankofengland.co.uk

‡University of Bristol. Email: Jonathan.Lee@bristol.ac.uk

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1 Introduction

Real estate property is one of the most vulnerable physical assets exposed to extreme weather events.[1] At the same time, it is one of the major vehicles of household wealth accumulation (Bhatia, 1987; Benjamin et al., 2004; Bach et al., 2020) and one of the major types of collateral in the financial system (Chaney et al., 2012; Ramcharan, 2020). Therefore, it is important to understand the implications of climate-related risks on property values in a world with an increasing frequency and intensity of extreme weather events.[2] While there is no lack of literature examining the effect of extreme weather events on property values (e.g. Hallstrom and Smith (2005); Beltrán et al. (2018)), much less is known about the role of public policies against extreme weather events in property markets. To address this gap, we exploit a novel empirical setting, the introduction of a UK public reinsurance scheme which provides cross-subsidized reinsurance to flood prone properties. Our findings highlight the hitherto unexplored effects of public reinsurance mechanisms against extreme weather events in affecting property prices and transaction volume.

The UK public reinsurance scheme, Flood Re, was introduced in April 2016. Its key policy objective is ensuring the availability and affordability of flood insurance to homeowners in flood prone areas (FloodRe, 2016).[3] In achieving this objective, Flood Re provides insurers with an option to pass the flood risk element of their policies on to the re-insurer, Flood Re, at a highly-discounted price. As a result, this reinsurance scheme reduces current and expected future insurance premiums for homeowners in flood risk areas. According to its 2020 annual report (FloodRe, 2020), Flood Re reports that 80% of households with previous flood claims found quotes that are more than 50% cheaper after the reinsurance scheme started operating. In terms of pound sterling, Flood Re is

[1]The UK Environment Agency estimates that one in every six properties, in total 5.2 millions properties, across England are at risk of flooding. The National Oceanic and Atmospheric Administration estimates that $106 billion worth of coastal property in the U.S. will be below sea level by 2050.

[2]Recent examples of catastrophic flooding include the the series of floods in western Germany in July 2021, causing over 200 deaths and over 4 billion euros insured losses; another example is the flood in Henan province of China in July 2021, leading to over 20 deaths.

[3]Another policy objective of the scheme is managing the transition to risk reflective pricing for flood insurance by the end of 2039.

estimated to reduce average annual insurance premium of flooded properties from around £650 to less than £325.[4] The report also finds that Flood Re increases availability of flood insurance among those households that were exposed to flooding.[5]

Beyond the introduction of Flood Re, the UK residential real estate market offers several characteristics which makes it an appealing laboratory to study the introduction of a public reinsurance scheme for flood risk. First, home-ownership rates in the UK are high. About two-thirds of households own a property, a higher proportion than Germany or France where only about every second household owns a property.[6] Hence, properties play a crucial role in wealth accumulation in the UK. Second, take-up rates of home insurance, which entail the coverage of flood risk, are very high, reaching over 95% in England (Surminski, 2018).[7] While this is a much higher take-up rate than the U.S., where only 12% of households have flood insurance (Hu, 2020), other countries like Belgium, France, Switzerland have a take-up rate comparable to the UK (CEA, 2009). Such a high take-up rate allows us to estimate the effect of Flood Re on property prices without explicitly looking at the level of insurance coverage. Third, information on the risk of flooding is publicly available to all participants of the real estate market. The UK Environment Agency (EA) has been publishing highly granular flood maps since 2008. Hence, not only insurance companies and mortgage lenders but also home owners and prospective buyers have access to this public information.

In this appealing setting, we examine three *ex-ante* uncertain questions. First, we study the effect of Flood Re, which reduces current and future insurance premiums of flood prone

[4] Information about average house insurance premiums of flooded properties is limited, the estimation is based on DEFRA (2013) which shows that the average household insurance premiums of flooded properties to be £650 before the introduction of Flood Re in 2010.

[5] The report finds that none of the household with prior flood claims received quotes from more than four insurers before the introduction of Flood Re, and 94% of them can receive quotes from five or more insurers after the introduction of Flood Re.

[6] The figure is similar to Spain and Netherlands. Information about home ownership rate of European countries is available at: *https://ec.europa.eu/eurostat/cache/digpub/housing/bloc-1a.html?lang=en.*

[7] In the UK, buildings insurance is required for getting a mortgage and the insurance coverage must at least covers the outstanding mortgage amount.

properties, on transaction prices. Second, we examine the distributional consequences of the introduction of the reinsurance scheme by estimating heterogeneous effects of Flood Re based on regional characteristics. Lastly, we study the effect of Flood Re on market liquidity by examining its effect on transaction volume of flood prone properties. We conjecture that the reduction in current and future insurance premiums increase the values and the transaction volumes of flood-prone properties. However, the actual effect depends on the expectation of the reduction in future insurance premiums caused by Flood Re, and the discount rate in discounting future insurance premiums. It is also uncertain how these factors vary across different demographic groups.

The major empirical challenge in identifying the effect of flood risk and the policy implementation on property values and transaction volume lies in isolating it from other confounding factors driving property prices.[8] We overcome this empirical challenge by leveraging a comprehensive data set of the population of all property transactions in England. The detailed geographical information of each transacted property allows us to compare price changes of properties within a small local area but with heterogeneous exposure to flood risk. The data set also allows us to control for the effect of other observable property characteristics (e.g. property type such as terraced, detached or semi-detached) on price. We use a repeat transaction approach comparing the same property transacted multiple times which allows us to further control for unobservable and time-invariant property characteristics. We are also able to differentiate the effect of price trends in local areas on property prices by comparing closely-located properties with different level of flood risk exposure sold in the same year of the current transaction and in the same year of the previous transaction.

We find that flood events reduce property values before the introduction of Flood Re. Yet, this negative effect is completely mitigated by the introduction of Flood Re. Results in our preferred specification suggest that a property experienced a flood longer than a day within four years before the property transaction experiences 1.6% reduction of property

[8] See Lustig and Van Nieuwerburgh (2005); Piazzesi et al. (2007) for other drivers of property prices.

values before the introduction of Flood Re. However, there is no reduction in the values of flooded properties after the introduction of Flood Re. On average, the introduction of Flood Re increases the value of flooded properties by GBP 4,083.[9] Our back-of-the-envelope calculation suggests that, among the 5.2 million properties that are at risk of flooding in England (Agency, 2009), the subsidization of Flood Re increases the total value of flooded properties by GBP 212.3 million per year assuming there is only 1% of the at-risk properties are flooded annually.[10] The total effect of Flood Re on property values would double to GBP 424.6 million if flood risk probability further increases to 2%.[11] We also find heterogeneous effects of Flood Re in different areas across England. The effect of Flood Re is stronger in areas with wealthier and older population, and urban areas, suggesting that the introduction of the scheme had distributional consequences. Importantly, the results highlight a plausibly unintended effect of Flood Re mainly benefiting wealthier households, in terms of the appreciation of property values. Lastly, we find that Flood Re increases the transaction volume of properties in at-risk areas. Our results suggest that a flooded property has 3.6% reduction in the annual probability of transacting before Flood Re came into place. Flood Re mitigates this negative effect on the transaction probability.[12]

To verify the relationship between property values and Flood Re, we conduct a set of placebo tests which employ the extension of an existing agreement between the government and insurance providers as a placebo treatment. We do not find any effect of the extension on property values. We also conduct simulations by testing the placebo effect of flood events and Flood Re on properties that are not actually flooded. These simulations suggest that our findings are unlikely driven by factors other than flood events and Flood Re. Our findings are also robust to two *ex-ante* measures of flood risk. We find that properties that are at flood risk and located near to river or sea are sold at discount before the introduction

[9]The average property price is GBP 226,840 and the calculation is based on the estimation results of our preferred specification shown in column 5 of Table 2: GBP 226,840 $\times$ 1.8% = GBP 4,083.

[10]The Environment Agency does not specify the average annual flood probability for those 5.2 millions at-risk properties. We therefore conservatively assume that all at-risk properties are on 100-year flood plain (i.e. 1% annual flood probability).

[11]i.e. 5.2m properties at risk $\times$ 1% risk $\times$ GBP 4,083 = GBP 212.3m.

[12]The base transaction rate in the sample is 14.6%.

of Flood Re. The results imply that our findings are not fully explained by the physical damages caused by the historical flood events, but also related to the expectation of future flood risk.

Our paper contributes to two strands of literature. First, our paper contributes to the growing body of literature examining the linkage between climate risk and government interventions. The increasing frequency and severity of extreme weather events motivate governments to enhance availability and affordability of extreme weather insurance. It therefore poses a question over the implications of these interventions. For example, Zahran et al. (2009) show that government implementation of flood risk mitigation measures increases flood insurance uptake; Hu (2020) finds that a national reform that publicises flood risk information across U.S. counties on the take-up rate of flood insurance. Closest to our paper, Sen and Tenekedjieva (2021) study the effect of the heterogeneous regulatory frictions in flood insurance pricing across U.S. states. They find that insurers overcome pricing frictions by cross-subsidizing insurance across states. A missing puzzle of Sen and Tenekedjieva (2021) is whether the cross-subsidization is capitalized into property values. Our paper addresses this gap by showing that the cross-subsidization induced by government interventions has implications beyond home insurance market. To the best of our knowledge, we present the first work that shows the effect of a public flood-reinsurance scheme on value and liquidity of properties at climate-related risk.

Our paper also relates to the broad literature examining distributional effect of public policy interventions (e.g. Beck et al. (2010); DeFusco and Mondragon (2020)). In particular, our paper contributes to the strand of this literature related to public policy interventions addressing environmental risk (e.g. Grainger (2012); Bento et al. (2015); da Silva Freitas et al. (2016); Isen et al. (2017)). More related to our study, few papers show the distributional effect of the National Flood Insurance Program (NFIP) in the United States. Making use of claim and premium data, Bin et al. (2012) find no evidence that the NFIP creates distributional effects on income measured at the county level. With similar approach and more recent data, Bin et al. (2017) show that the net premium (premiums-payouts) of the NFIP is regressive, implying that the NFIP disproportionally benefits wealthier segments of population. While the two papers focus on the progressivity of the NFIP, they do not study the redistributional effect of the NFIP in terms its impacts on property values. Our paper addresses this gap by documenting that the mitigating effect of a public flood reinsurance scheme on at-risk properties are much stronger among richer households. The results provide an unique insight in examining the objectives of public flood reinsurance schemes and other policy interventions in mitigating environmental risk.

The rest of the paper is structured as follows. Section 2 summarizes the policy background of Flood Re; section 3 present the conceptual framework and empirical strategy; section 4 details the data of our analysis; section 5 discusses the results; section 6 concludes.

2 Background on the policy

Since the 1960s, there had been a series of "Gentlemen's Agreements" between the UK government and the insurance industry to ensure the availability of flood insurance in flood-prone areas. These agreements were based on the mutual commitment between the insurers providing insurance in high risk areas and the government increasing investments in flood defenses. They formed the foundation for flood insurance for the next 40 years, until an unprecedented series of floods hit between 1998 and 2000.[13]

Despite of these agreements, the losses from the series of floods caused insurers to be more prudent in underwriting flood insurance, leading to many flooded households finding

[13]Sustained heavy rain in Midland from 9 April to 10 April 1998 led to severe flood. Approximately 4,200 properties were inundated and economic losses were estimated to be GBP 350 million (MetOffice, 2012). The autumn of 2000 was the wettest on record since 1766. over 10,000 properties were flooded across the country, and transportation services were severely disrupted, causing economic losses over GBP 1 billion (EnvironmentAgency, 2001).

it difficult to renew their policies in 2000 (Dlugolecki, 2000). On the one hand, fueled by increasing media attention and widespread criticism over the UK government's responses to the series of floods, it was pressurized to formalize an agreement with the insurance industry to ensure the availability of flood insurance. On the other hand, the insurance industry took this opportunity to request for the right to refuse insuring the highest risk areas and to adjust insurance premiums according to the level of flood risk. Under this circumstance, the formal policy agreements "Statement of Principles on the Provision of Flood Insurance" (SoP) was agreed by the representative of all insurance companies in the UK, Association of British Insurers (ABI), and the government in 2002. Under the SoP, insurers were obligated to provide flood insurance. However, properties in the highest flood risk categories , those with annual flood probability above 1.3%, were excluded in the SoP. Moreover, properties built after 2009 were also excluded since the revision of the SoP in 2004. The government, in return, promised to invest in flood risk mitigation measures.[14] While the SoP addressed the issue of the availability of flood insurance, it remained silent on affordability. There was no restriction on the size of the insurance premiums. Therefore, any increase in premiums did not violate the SoP but could risk that insurance might become unaffordable for homeowners.

In the 1990's and early 2000's, as map technology and computing power were still underdeveloped, insurance firms found it difficult to measure flood risk. Therefore, flood risk was largely not priced into insurance premiums until the introduction of a flood risk map published by the Environment Agency (EA) in 2004. With the increasing frequency of extreme flood events, concerns about affordability of flood insurance and its implications for mortgage affordability was growing since then. Coming close to the expiration of the SoP in 2013, the insurance industry and the government agreed on creating a reinsurance scheme, Flood Re, to replace the SoP. Flood Re has two major purposes. The first purpose is to promote both the availability and the affordability of flood insurance. The second purpose is to provide a smooth transition to risk reflective pricing for flood insurance.

[14]See Butler and Pidgeon (2011) for discussions on flood risk mitigation measures adopted by the UK government.

After extending the SoP for another three years in 2013, Flood Re was approved by the parliament in 2014. It started operating in April 2016 to replace the SoP (Surminski and Eldridge, 2017). Flood Re is planned to be phased out in 2039 when the flood insurance market fully transitions to risk-reflective pricing.

Flood Re lowers the cost of providing flood insurance in high risk areas by providing an option for insurers to reinsure policies at a subsidized price which only increases with the tax banding of the insured property. The subsidies are covered by the insurers through an annual levy which is estimated to pass on all insurees for £10.50 per policy (Surminski, 2018). Flood Re is eligible for properties at all flood risk levels. However, properties built after 2009 are excluded to discourage the development of new properties in flood risk areas.[15] Since insurers can now pass on their risk for subsidized price for properties at all flood risk level, Flood Re has increased the availability and reduced the cost of flood insurance in high risk areas (FloodRe, 2020).

In terms of the awareness of Flood Re, survey data of 2018 "Availability and Affordability of Insurance report" suggests that 45% of the respondents in flooded areas are aware of Flood Re, while only 29% of the respondents in non-flooded areas are aware of Flood Re (see Figure 1). Under the design features of Flood Re, households cannot influence insurers' decision to pass on the flood risk component of the insurance contract. Hence, households' awareness of Flood Re does not influence the degree to which this reinsurance scheme affects house prices. Figure 2 (Crick et al., 2018) outlines the mechanism of Flood Re and the relationship between government and industry.

[15]Despite of that, a large number of properties are still being built in flood prone areas, particularly in deprived neighbourhoods (Rözer and Surminski, 2021).

3 Conceptual framework and empirical strategy

In this section, we provide a simple conceptual framework which supports our understanding of the mechanism of the introduction of Flood Re on property values. Based on the framework, we develop the empirical strategy.

3.1 Conceptual framework

To start with, we consider a simple, one period hedonic pricing model according to which a class of differentiated products is completely described by a vector of measured characteristics (Rosen, 1974). Hence, the price of a property can be characterized by a function of observable property characteristics z, e.g. whether it is a flat or house. It is reduced by the insurance premium which a home owner pays. This insurance premium is itself a function of flood risk the property is exposed to:[16]

$$Property\,price(z, Premium, Flood\,risk) = f(z) - Premium(Flood\,risk) \tag{1}$$

From equation 1, it can be seen that higher flood risk decreases property price via higher insurance premium. In mathematical terms, the derivative of property price with respect to flood risk is the negatively proportional to the derivative of insurance premium with respect to flood risk, i.e. $\frac{\partial Property\,price}{\partial Flood\,risk} = -\frac{\partial Premium}{\partial Flood\,risk}$.

In absence of a public reinsurance scheme such as Flood Re, insurance companies have a strong incentive to price flood risk into insurance premium, i.e. the derivative of premium with respect to flood risk is positive, $\frac{\partial Premium}{\partial Flood\,risk} > 0$. As property price is a function of insurance premium, the derivative of property price with respect to flood risk is negative, $\frac{\partial Property\,price}{\partial Flood\,risk} < 0$. Hence, we expect to observe higher flood risk to be associated with lower property price.

[16] There is a number of other potential factors affecting insurance premium, such as property structure and claim record. For simplicity, we assume insurance premium is only affected by flood risk of a property.

After the introduction of Flood Re, insurance companies can transfer the flood risk component of their policies to Flood Re. Therefore they have limited incentives to price flood risk into premiums. Thus, we expect the derivative of premium with respect to flood risk to be zero, $\frac{\partial Premium}{\partial Flood\,risk}$ =0. As a result, property price is no longer sensitive to flood risk, $\frac{\partial Property\,price}{\partial Flood\,risk}$ =0.

In our empirical analyses, we examine these conjectures by testing the change in the derivative of property price with respect to flood risk after the introduction of Flood Re, detailed in section 3.2.

3.2 Empirical strategy

We estimate the following equation to identify the effect of flood risk on property prices, more importantly, the mitigating effect of Flood Re:

$$\begin{aligned}\Delta Price(ln)_{i,g,t} = Price(ln)_{i,g,t} - Price(ln)_{i,g,t-1} = \beta_0 + \beta_1 Flood\,Risk_{i,g,t} + \\ \beta_2 Flood\,Risk_{i,g,t} \times Post\,Flood\,Re_t + \gamma X_{i,g,t} + \delta_{g,t} + \delta_{g,t-1} + \varepsilon_{i,g,t}\end{aligned} \tag{2}$$

where $\Delta Price(ln)_{i,g,t}$ is the outcome variable, calculated as the difference between $Price(ln)_{i,g,t}$, the natural logarithm of the value of the property i in 3 digit post code g in year t in the current transaction and the natural logarithm of the value of the same property in the previous transaction, $Price(ln)_{i,g,t-1}$.[17]

$Flood\,Risk_{i,g,t}$ indicates flood risk of property i, its coefficient β_1 captures the derivative of property prices with respect to flood risk discussed in Section 3.1, $\frac{\partial Property\,price}{\partial Flood\,risk}$, before

[17] An alternative strategy is comparing the change in transaction prices between flooded properties that are eligible and ineligible to Flood Re. However, eligibility of Flood Re depends on the built year of properties and built year reflects the change in building standard in terms flood resilience, particularly properties built after 2002 (see discussion in section 4.2). Therefore, we expect the hypothetical effect of flood event and Flood Re to be different between the eligible and ineligible properties, leading to the underestimation of the mitigating effect of Flood Re.

the introduction of Flood Re. We employ different flood risk indicators. The primary measurement is a dummy variable $Flooded_{i,g,t}$ which indicates whether the property experiences at least one flood event lasting for more than a day four years before the transaction and a dummy variable $Flash\,flooded_{i,g,t}$ which equals to one if the property only experiences flood event last for a day four years before the transaction. The second measurement is a dummy variable, $Risk(L + M + H)_{i,g}$, indicating if the flood risk category of the property is above "very low". The third measurement is a dummy variable, $Distance\,to\,water(< 100m)_{i,g}$, indicating whether the property is within 100 meters of river or sea. $Post\,Flood\,Re_t$ is a dummy variable indicating whether the property transaction is after the implementation of Flood Re.

The interaction term, $Flood\,Risk_{i,g,t} \times Post\,Flood\,Re_t$, is our variable of interest, the coefficient, β_2, captures the effect of Flood Re on the prices of at-risk properties. The derivative of property price with respect to flood risk after Flood Re is therefore measured by the sum of β_1 and β_2 in equation 2. A negative β_1 and a positive β_2 with similar magnitude support the conjecture that Flood Re mitigates the negative effect of flood risk on property prices, i.e. reducing the magnitude of the derivative of property price to flood risk to 0. $X_{i,g,t}$ is a vector of control variables, reflecting property characteristics, i.e. property type, year of construction and form of tenure (freehold vs. leasehold).

$\delta_{g,t}$ and $\delta_{g,t-1}$ are fixed effects of the 3-digit postcode $\times$ year of the second transaction and 3-digit postcode $\times$ year of the previous transaction respectively. $\delta_{g,t}$ and $\delta_{g,t-1}$ capture further confounding factors, such as the supply of new properties, affecting property values in the 3-digit postcode areas in the years of current and previous transaction[18]; $\varepsilon_{i,g,t}$ is the error term. We cluster standard errors are at the local authority level.

One might argue that equation 2 is plausibly insufficient in capturing the effect of price trend in local property markets because the fixed effects, $\delta_{g,t}$ and $\delta_{g,t-1}$, in equation 2 might

[18]Each 3-digit postcode contains on average around 6,000 properties (Garbarino and Guin, 2021).

not precisely capture the price trend within the time interval between the two transactions of each property. To address this concern, we estimate equation 3 which control the interactions of $\delta_{g,t}$ and $\delta_{g,t-1}$. The interaction, $\delta_{g,t} \times \delta_{g,t-1}$, allows us to isolate the effect of flood risk and Flood Re on flood-prone properties from other confounding factors and price trend driving value of all properties within the same 3-digit post code area whose current and previous transactions are in the same respective years.

$$\begin{aligned} \Delta Price(ln)_{i,g,t} = Price(ln)_{i,g,t} - Price(ln)_{i,g,t-1} = \beta_0 + \beta_1 Flood\,Risk_{i,g,t} + \\ \beta_2 Flood\,Risk_{i,g,t} \times Post\,Flood\,Re_t + \gamma X_{i,g,t} + \delta_{g,t} \times \delta_{g,t-1} + \varepsilon_{i,g,t} \end{aligned} \tag{3}$$

4 Data and Sample

4.1 Data

To implement our empirical strategy, we employ three different data sets. The first data set includes property transaction, the second data set contains the measurements of property flood risk and the third data set includes the characteristics of local authority districts.[19] We describe these three data sets below.

4.1.1 HM Land Registry Price Paid Data

We use Price Paid Data (PPD) from HM Land Registry, which covers the universe of transactions of residential properties in England and Wales since 1995. This data set was used by several researches in studying the UK property market (e.g. Giglio et al. (2015);

[19] Local authority district is a level of administrative division of England. There are a total of 343 local authority districts in England, comprising five types of local authority: county councils, district councils, unitary authorities, metropolitan districts and London boroughs.

Bracke and Tenreyro (2021)). It provides information on the exact address of each property, the transaction date and the transaction price and the property characteristics.[20] The set of geographical information and property characteristics allows us to differentiate other confounding factors driving property values. This data set does not differentiate whether the transacted property is buy-to-let or buy-to-live. However, the difference in buying purpose should not affect our results as homeowners are in charge for repairs and restoration of the flooded properties even when they let their properties. Hence, buying purpose should not affect the incentive of homeowners to get their properties insured.

4.1.2 Recorded Flood Outlines

Our primary measurement of flood risk is based on historical flood events. We employ the Recorded Flood Outlines produced by the Environment Agency to identify flood history of each property. The Recorded Flood Outlines records historic flooding from rivers, the sea, groundwater and surface water since 1946 as GIS layers.[21] To match them with the property transaction data set, we map these layers to 6-digit postcode units.[22] For the purpose of this paper, the data records the exact dates of the start and end of each flood outline. This allows us to calculate the duration of each flood event and the time interval between each property transaction and the latest flood event experienced by the respective property. To highlight the differential effect of flood events on property values, we identify property as "flooded" if there is at least a flood event lasting for more than a day within the four years before the transaction and we identify property as "flash-flooded" if there are only flood events lasting for a day within the four years before the transaction. The locations of the "flooded" properties are depicted in Figure 3. It shows that most of the flooded properties are clustered in North West, Yorkshire and the Humber, South West and South East. Midlands and East of England are less exposed to flood events.

[20] The property characteristics include property type (Detached or Semi-detached or Terraced or Flat or Other); whether the property is new-built; and the forms of tenure (Freehold or Leasehold).

[21] Completeness of the data in early years was questionable, but it has improved over the years and flood events in recent years, including our sample period, were well-recorded.

[22] 6-digit postcode covers a small area which on average only have 15 properties and there are around 1.7 million postcodes in the UK.

4.1.3 Flood Map

In this paper, we use the flood map published by the Environment Agency. Compared to actual flood events, this flood map offers an estimate of the *ex-ante* flood risk of properties. It indicates the number of property in each flood risk categories per 6-digit postcode unit.[23] The map has been available online and updated annually since 2004.[24] For our analysis, we use the 2016 version of this flood map. Similar to Garbarino and Guin (2021), we calculate the midpoint of the flood risk probability for each risk category in order to calculate an average annual flood probability of all properties in a 6-digit post code. In the paper, we identify those properties in 6-digit post codes with an average annual flood probability of more than 0.1% as at-risk property. The locations of these properties are shown in Figure 4. It shows that at-risk properties are clustered in similar areas that have been exposed to flood events, i.e. most of the flooded properties are clustered in North West, Yorkshire and the Humber, South West and South East. It also shows that there are more at-risk properties than properties that are actually flooded, as shown by Figure 3.

4.1.4 Distance to water

As another alternative measurement of flood risk estimates flood risk based on the distance to water. Specifically, we calculate the shortest distance between each 6-digit postcode to a river or the sea, whichever the distance is shorter. We classify those properties that are within 100 meters to water as at-risk properties. Figure 5 shows the locations of these properties, suggesting that properties that are near to a river and the sea are scattered in different parts of England, apart from the areas connected to Wales and Scotland.[25]

[23] There are four categories in 2016 flood map: very low (one-year ahead flood probability less than 0.1%), low (between 0.1% and 1%), medium (between 1% and 3.3%) and high (greater than 3.3%)

[24] Although the Flood Map is updated annually, the variations across year are rather limited, apart from a major update in 2013-2014 (Garbarino and Guin, 2021).

[25] A caveat of this measurement is that it does not consider elevation. But we argue it would only marginally affect the classification of at-risk properties, because it is rather rare that elevation tremendously increases within 100 meters.

4.1.5 Local authority characteristics

To examine the heterogeneous effects of Flood Re in different areas, we employ the English Indices of Deprivation. It allows us to measure the deprivation level of local authorities, the population estimates by the Office of National Statistics to measure proportion of population with National Qualifications Framework (NQF) level 4 or above qualification (e.g. degree with honours and postgraduate certificate), average income and age of local authorities; 2001 Rural-urban classification produced by the Office for National Statistics to differentiate urban and rural areas; general election results recorded by the House of Common to measure the percentage of votes for the Green Party in local authorities in the 2019 United Kingdom general election; and EU referendum results recorded by the Data.gov.uk.[26]

4.2 Sample construction

The initial sample starts with the universe of all property transactions in England between 1995 and 2020. The first step of sample filtering addresses the concern over the change in the public planning of new buildings after the publication of the Planning Policy Guidance Note 25 (PPG25) (DTLR, 2001). The PPG25 required local planning authorities to employ a set of decision rules accounting for flood risk. It also required them to consult with the Environment Agency (EA) on approvals for permissions to build in areas at the risk of flooding. As a results, the EA rejection rate of development permission on flood risk ground increased from 10% in 2001 to 22% in 2002, and further increased to 33% in 2004 (Porter and Demeritt, 2012). Properties built after the publication of the PPG25 are therefore expected to be less prone and more resilient to flood risk. To alleviate this concern, our sample excludes properties built after 2002.

[26]Because the seven local authority level variables are produced in different years and the classification of local authority changes over time, a very small number of observations in the property transaction data set fail to match with the measurements.

To examine the price change of the same property over time, we construct the subsample of properties that were transacted at least twice since 1995 and at least one transaction is in the sample period which covers the four years before and after Flood Re. We then convert the data into panel structure by identifying the series of transactions of the same property by using address information.[27] After taking first difference of the transaction price, it results in 1,754,067 observations of 1,563,062 properties. With this sample, we then match the three flood risk indicators with the 6-digit postcode units and match local authority-level variables with the local authority identifier.

Summary statistics of the sample are shown in Table 1. In Panel A, we present the summary statistics of property-level variables. The average property price in our sample is GBP 226,840 with a growth rate of 42.4% between transactions. The appreciation of properties is rather large because of the long time interval between transactions. The average transaction time interval of a property in the sample is around eight years and four months. For property characteristics, a small proportion of properties are newly built at the time of the previous transaction. The majority of properties in the sample is detached, semi-detached or terraced, and around 15% of them are flats. Regarding the tenure type, a large majority of the properties are freehold and the remaining are leasehold. In Panel B, we show the summary statistics of the different flood risk measurements. There are around 0.3% of observations experience at least one flood event last for more than a day four years before property transaction and 0.1% of observations experience only flood event(s) last for a day four years before property transaction. 11% of properties are classified as at-risk properties in terms of the annual probability of being flooded and 7.5% of properties are located within 100 meters of river and sea. In Panel C, we summarize the seven local-authority level characteristics used for sample-split tests.

[27] Restricting the pre-Flood Re period to four years mitigates the concern that our findings are simply driven by the improvement of flood defence over time, which could potentially explain why the effect of flood event on property prices disappear in the later years of the sample period (post-Flood Re period).

5 Results

5.1 Effect of flood events and Flood Re on property prices

This section starts with examining the average effect of flood and flash flood on property prices over the sample period. Without differentiating the period before and after the implementation of Flood Re, we expect the negative effect of flood events to be underestimated because Flood Re is expected to mitigate the negative effect of flood on property values. This exercise allows us to compare the estimation results after introducing the variable that differentiate the sample period after the implementation of Flood Re from the period before the implementation of Flood Re. Column 1 in Table 2 presents the estimation results of equation 2 without interacting $Flood\,Risk_{i,g,t}$ with $Post\,Flood\,Re_t$ and without any property level control variables. The results confirm some previous findings (Lamond and Proverbs, 2006; Kousky, 2010; Bernstein et al., 2019), suggesting that flooded property experience a 0.9% (t-statistics -2.21) decrease in property prices, while there is no effect of flash flood on property prices, reflecting the salience of flood events affects the impacts on property values.

We then introduce the variable $Post\,Flood\,Re_t$ into the estimations to differentiate the effect of flood after the introduction of Flood Re from before the introduction of Flood Re. The estimation results are shown in column 2-5 of Table 2. The interaction term, $Flooded_{i,g,t} \times Post\,Flood\,Re_t$, indicates whether Flood Re plays a role in mitigating the negative effect of flood events, a positive coefficient suggests that Flood Re mitigates the effect of flood events on property values. Apart from the interaction term, we also expect the introduction of the interaction term $Flooded_{i,g,t} \times Post\,Flood_t$ to increase the magnitude of the estimated coefficient of $Flooded_{i,g,t}$, comparing with the results in column 1.

Estimation results in all specifications consistently suggest that flood events lower property prices and Flood Re completely mitigates the negative pricing effect. Consistent with the findings in column 1, there is no evidence that flash floods affect property prices in either periods (before and after the implementation of Flood Re). Column 2-3 present the estimation results of equation 2. In column 2, the results suggest that flood event longer than a day reduces property values by 1.8% (t-statistics -3.14) before Flood Re and the negative effect reduces to only 0.3% after the introduction of Flood Re. Column 3 presents the results with property control variables. The inclusion of the control variables generates similar results, although the coefficients of $Flooded_{i,g,t}$ and $Flooded_{i,g,t}$ x $Post\,Flood_t$ are slightly reduced. Columns 4-5 show the estimation results with our preferred specification in equation 3, introducing the interaction of $\delta_{g,t}$ and $\delta_{g,t-1}$ in the specification. Column 4 presents the results without control variables and column 5 shows the results with control variables. The results are similar to column 2-3. Column 4 shows that the value of flooded properties drops by 2.1% (t-statistics -3.39) before Flood Re and the negative effect of flood on property prices reduces to only 0.2%. With control variables, column 5 shows that a flooded properties experience a 1.6% drop in value. The estimated coefficient of the variable, $Flooded_{i,g,t} \times Post\,Flood$, is 0.018 ($t$-statistics 2.68), suggesting that flood events do not reduce property values after the implementation of Flood Re.

5.2 Falsification tests

To examine whether property prices are indeed affected by Flood Re, we conduct two falsification tests. The first test relates to the introduction of Flood Re.[28] The second test then relates to flood events.

In the first test, we redefine the sample to property transactions in April 2010 to April 2016 and use the extension of the Statements of Principal (SoP) in July 2013 as a placebo treatment to flooded properties. We replace the variable $Post\,Flood\,Re_t$ in equation 2 and 3 with $Post\,SoP\,extension_t$, which equals to 1 if the transaction is after July 2013 (0

[28]It implicitly tests whether there are announcement effects.

otherwise).

This specification estimates how the SoP extension affects flooded property prices. Because the SoP had already been in place before the extension, it should not affect flooded property prices. Different specifications in column 1-4 in Panel A of Table 3 shows that the interaction term is not different from zero, suggesting that value of flooded properties is unaffected by the placebo treatment.

In the second falsification test, we employ the genuine Flood Re introduction date but verify the effect of flood treatment. Specifically, we constrain the sample to properties that are not being flooded in the past four years of transactions. We then randomly assign properties to be "flooded" properties and replicate the estimation equation 3. We then run Monte Carlo simulations with 1,000 replications of equation 3 to check whether non-flooded properties are affected by Flood Re.

This exercise estimates how non-flooded properties affected by Flood Re. Because Flood Re should not affect properties that are not at flood risk, the null of zero effect is true. Thus, we should only reject the null by making Type 1 errors. Panel B of Table 3 shows that the rejection rates are in line with those that would occur through Type 1 errors. In most cases, the average value the coefficients of $Pseudo\,flood_{i,g,t}$ and $Pseudo\,flood_{i,g,t} \times Post\,Flood\,Re_t$ are close to 0, suggesting that non flooded properties are unaffected by Flood Re.

5.3 Heterogeneous effects of Flood Re

In this section, we examine the heterogeneous effects of flood and Flood Re on property prices. Specifically, we examine whether Flood Re has different effects in subsamples, e.g. across property values and across different regions.

5.3.1 Demographic characteristics

To start with, we provide evidence on the heterogeneous effects of Flood Re in terms of property values. To do so, we replicate the estimation in column 5 of Table 2 with samples of specific percentiles of the property prices in the first transaction.[29] Figure 6 shows the estimated coefficient and 95% confidence interval of the variable $Flooded_{i,g,t}$ x $Post\,Flood_t$ in each sub-sample. We find that Flood Re has a stronger effect on more expensive properties (properties whose value is higher than the 60^{th} percentile ($p60$) of property prices in the sample) and having limited effect on lower-value properties (properties whose value is lower than or equals to the $p60$ of property prices in the sample). Yet the figure does not inform the population characteristics of areas benefited more from Flood Re.

We then go on and provide a richer picture on the heterogeneous effects of Flood Re. To do so, we combine different local authority level indicators with property transaction data. Then we split the sample based on the median value of each indicator (apart from the urban/rural indicator) and replicate the estimation of equation 3.[30] The results in this section inform us whether the effects of flood and Flood Re are stronger in certain areas, and whether the difference is statistically significant. While the results in this section shed light on different channels leading to the heterogeneous effects, we do not seek to fully disentangle the different channels without any more granular data.

First, we examine the heterogeneous effects of Flood Re in terms of income levels. The result is important to evaluate the policy objective of Flood Re. With the aim of promoting affordability of flood insurance, the targeted beneficiaries of Flood Re should be the lower income groups. However, social class often reflects the differences in financial sophistication and awareness of climate risk (Fielding and Burningham (2005); Fielding (2012)). The differences could eventually lead to the heterogeneous effects of Flood Re in different social classes. We employ average income level of local authority district to examine this

[29]The specified percentiles used in the estimations are $p20$, $p40$, $p60$, $p80$ and $p100$.
[30]The correlation matrix of the indicators is shown in Table A.2 in the appendix.

conjecture. In Table 4, column 1 (2) shows the estimation results with the properties in the local authorities with higher (lower) average income. The results suggest that local authorities that have higher average income have a stronger negative effect of flood event on property prices. More importantly, the coefficients of $Flooded_{i,g,t} \times Post\,Flood_t$ across the two columns suggest that the households with higher income benefit more from Flood Re through the appreciation of property values. The Chow test F-statistics verify that the coefficients of the two groups are significantly different at 5% significance level.

To address the concern that income is an unreliable measure of deprivation and poverty (Ringen, 1987, 1988), we employ the English indices of deprivation to more accurately measure deprivation. Apart from income, these indices of deprivation provide an all-rounded measurements of deprivation which takes into account of other six domains of deprivation, including employment, education, health, crime, barriers to housing and local services, and living environment.[31] Column 3 (4) presents the estimation results with the properties in the more (less) deprived local authorities. Consistent with the results in column 1-2, the results suggest that local authorities that are less deprived have a stronger negative effect of flood event on property prices and the less deprived households benefit more from Flood Re. The Chow test F-statistics also suggests that the coefficients of the two groups are significantly different at 5% significance level. Taken the results of the first and second set of sample split together, we show that Flood Re disproportionately benefit wealthier households, in terms of the appreciation of flood-prone properties' value.

The next set of sample split builds upon the finding that the awareness of Flood Re is positively related to age.[32] Because the older people are more aware of the introduction of Flood Re, we expect the effect of Flood Re is stronger in areas with a higher average age. Consistent with the finding in the survey data, columns 5-6 in Table 4 suggest that

[31] See Payne and Abel (2012) for more details of the background and computation method of the English indices of deprivation.

[32] We employ the survey data of the 2018 Availability and Affordability of Insurance report conducted by the DEFRA to examine the correlation between different demographic characteristics and the awareness of Flood Re. We find that older respondents in at risk areas are more likely to know Flood Re. The results are presented in Table A.3 in the appendix.

effect of flood events are similar across older and younger group, but the effect of Flood Re is stronger in the areas with older households. Column 5 shows that flooded property in local authorities with older households sell at 2.1% discount and the introduction of Flood Re completely mitigate the negative effect. Column 6 shows that flooded property in local authorities with younger households sell at a 1.7% discount and the introduction of Flood Re has no effect on the value of flooded properties. The Chow test F-statistics verifies that the coefficients of the two groups are significantly different at 5% significance level. The results imply that the difference in the awareness of Flood Re affects its impact on property values.

Education levels plausibly reflect households' financial sophistication and awareness of public policy change. If that is true, Flood Re could have a stronger impact in higher educated areas. In column 7 and 8, we find that areas with more educated population have a stronger effect of Flood Re on flooded properties value, however, the Chow test F-statistics suggest that the difference in coefficients is statistically insignificant at 10% level.

We then examine the heterogeneous effects of flood risk and Flood Re in urban and rural areas. Due to the subtle differences in property market structure, characteristics of properties, demographic composition and types of flooding in urban and rural areas, the effect of flood and Flood Re in urban areas could be different from rural areas. If this is the case, Flood Re could imply a wealth redistribution among urban and rural population. For example, Beltrán et al. (2019) show that the value of rural properties is less affected by flood events. In column 9-10 of Table 4, we find that both the effect of flood and Flood Re is stronger in urban areas. The Chow test F-statistics suggests that the coefficients of the two groups are significantly different at 1% significance level.

5.3.2 Revealed believes

Heterogeneous beliefs in climate risks affect property values. Baldauf et al. (2020) find that value of properties at climate risk in areas with more believers of future climate risk are more likely to sell at discount. We therefore expect that areas with greater concern of climate risks respond stronger to flood risk and Flood Re.

We employ the percentage of votes for the Green Party in the 2019 United Kingdom general election results to measure the differences in belief of climate change risk across local authorities. If awareness of climate risk is the driver of the heterogeneous effects, the effect of flood and Flood Re is expected to be stronger in local authorities with higher share of votes to the Green Party. Column 1-2 in Table 5 present the estimation results. Surprisingly, the Chow test suggests that there is no significant difference across the two groups. Apart from the Chow test, the coefficients of the two key variables, $Flooded_{i,g,t}$ and $Flooded_{i,g,t} \times Post\,Flood\,Re_t$, are similar across the two groups, despite of the lower statistical significance in the group with more votes for the Green Party. The results imply that the differences in concern in climate risk do not explain the heterogeneous effects of Flood Re across different local authorities.

A survey conducted by Savanta ComRes suggests that Brexit voters are almost twice as unlikely to believe in climate change risk.[33] We therefore use the vote results for Brexit as an alternative measurement of average level of climate risk concern on local authority level. The results in column 3-4 suggest that areas with higher vote percentage for Brexit show a stronger impact of Flood Re, yet the Chow test suggests that the differences in coefficients among the two sub-group are statistically insignificant at 10% significance level.

[33] Details of the survey can be found on https://comresglobal.com/polls/assaad-razzouk-eu-referendum-and-science-poll/.

5.4 Alternative measurements of flood risk

In this section, we show that our findings are robust to alternative measurements of flood risk. In panel A of Table 6, we use the the flood risk categories in the flood map of the Environment Agency to measure *ex-ante* flood risk of properties. Properties that are in the flood risk categories above "very low" are classify as at-risk properties. The results are similar across different specifications in column 1-4. In the preferred specification in column 4, we find that property at flood risk decrease 0.4% (t-statistics -3.11) in value before Flood Re, but the negative effect disappears after the introduction of Flood Re.[34]

Panel B of Table 6 employs distance to water (source of water is either river or sea) as another alternative measurement of flood risk. We classify properties located within 100 meters of water as at risk properties. The results are still consistent across different columns. In the preferred specification in column 4, we find that properties located within 100m of sea or river sell at a discount of 0.8% (t-statistics -7.04) before the introduction of Flood Re and this negative effect is mitigated by Flood Re.

In the appendix, we replace the dummy variables of the three categorical measurements of flood risk with continuous measurements, namely duration of flood, flood risk probability and distance to water. We find consistent results. The results in Table A.6 suggest that the negative effect increase with the severity of flood risk measured by the 3 continuous measurements. In all three continuous measurements, Flood Re mitigates the negative effect of flood risk on property values.

5.5 Effect on trade volume

The discount of flood prone property could have an implications on transaction volume. Following the loss aversion consideration in Genesove and Mayer (2001), owners of

[34]We also employ this *ex-ante* measurement of flood risk to replicate the sample split tests discussed in the previous section, the inferences remain unaffected. The results are shown in Table A.4 and A.5 in the appendix.

flood-prone properties may defer selling the flooded properties until the effect of flood fades away over time. If this is the case, we should expect recently flooded properties are less likely to be traded, and this effect should be mitigated by the introduction of Flood Re. To examine the changes in transaction volume accompanying flood events and the introduction of Flood Re, we follow Bernstein et al. (2019) to expand the original sample into a balanced panel data set (i.e. each property has an observation in each year of the sample period) to estimate the following equation 4:

$$\begin{aligned} Trade_{i,g,t} = \beta_0 + \beta_1 Flooded_{i,g,t} + \beta_2 Flooded_{i,g,t} \times Post\,Flood\,Re_t + \\ \beta_3 Flash\,flooded_{i,g,t} + \beta_4 Flash\,flooded_{i,g,t} \times Post\,Flood\,Re_t + \gamma X_{i,g,t} + \delta_{g,t} + \varepsilon_{i,g,t} \end{aligned} \tag{4}$$

where $Trade_{i,g,t}$ is the outcome variable, indicating whether the property is traded in year t, $Trade_{i,g,t}$=1 if property i is traded in year t, 0 otherwise. $\delta_{g,t}$ captures the confounding factors affecting the property of being traded in the 3-digit postcode g in year t. Definitions of other variables follow equation 2.

In column 1 of Table 7, we start with examining if being flooded within the past 4 years reduce the probability of being transacted by estimating equation 4 without the interaction terms. Consistent with our expectations, the results show that flooded properties are 0.5% less likely to be transacted (from a base transaction rate of 14.6%). The results also suggest that flash flood does not affect the probability of transaction. We then introduce the interaction terms of $Flood\,Risk_{i,g,t} \times Post\,Flood\,Re_t$. The results are similar irrespective of the inclusion of property control variables (shown in column 2 and 3 of of Table 7). The results with control variables are shown in column 3, suggesting that flooded properties are 3.6% less likely to be transacted in the following four years of flood (from a base transaction rate of 14.6%), but Flood Re not only mitigates the negative effect, it increases the transaction probability by 2.4%. The results plausibly reflect the sales of the accumulated properties that were flooded before the introduction of Flood Re.[35]

6 Conclusion

In this chapter, we examine how the introduction of a public reinsurance scheme, Flood Re, in the UK affects value and liquidity of properties at flood risk. Our results suggest that Flood Re mitigates the negative effect of flood risk on property prices and transaction volume. We also find that Flood Re has heterogeneous effects on property prices in different areas. The effect on property prices are stronger in urban areas and areas with wealthier, older and less deprived populations. Yet we do not find strong evidence that the effect of Flood Re are different in terms of their climate-related preferences, revealed by voting outcomes in the 2019 general election and the 2016 United Kingdom European Union membership referendum.

Our paper offers two key policy implications. First, the results highlight the transition risk of public policy interventions. Flood Re is planned to phase out in 2039. The flood risk component of property insurance is therefore expected to be fully priced into premiums by that time. Consequently, value of properties at flood risk may experience a sudden adjustment, reflecting the increase in current and future premiums, which can disrupt property and financial markets. Second, our results highlight the plausibly unintended distributional consequences of Flood Re. While Flood Re is expected to help lower-income households, our results suggest that Flood Re has a weak impact in lower income and more deprived areas but a stronger impact in higher income and and less deprived areas. This finding provides an unique insight in examining the effectiveness of Flood Re and the design of future public policies in mitigating climate risk.

[35] Apart from the probability of trade, we also find that flooded properties are being traded later than non-flooded properties, and Flood Re completely mitigates this effect. The results are shown in Table A.7 in the appendix, we temper the interpretation of the results because this test plausibly suffers from reverse causality between the probability of being flooded and the time interval between transactions.

There are potential research directions that are beyond the scope of this chapter because of the data limitations. Particularly, future work can identify and differentiate the channels in driving the heterogeneous impacts of Flood Re in different demographic groups. Is it because of the difference in financial sophistication or awareness of future climate risk or local property market structure or other potential channels?

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7 Tables and figures

Table 1: Summary statistics

Variable	N	Mean	Std. Dev.	p5	p95
Panel A: Property variables					
Property price (ln)	1,754,067	12.332	0.618	7.313	19.163
D. Property price (ln)	1,754,067	0.424	0.33	-0.019	1.249
New built$_{t-1}$	1,754,067	0.029	0.169	0	1
Property type:					
Detached	1,754,067	0.233	0.423	0	1
Semi-detached	1,754,067	0.288	0.453	0	1
Terraced	1,754,067	0.319	0.466	0	1
Flat	1,754,067	0.153	0.36	0	1
Other	1,754,067	0.008	0.087	0	1
Tenure:					
Freehold	1,754,067	0.801	0.399	0	1
Leasehold	1,754,067	0.199	0.399	0	1
Panel B: Flood risk variables					
Flooded	1,754,067	0.003	0.059	0	1
Flash-flooded	1,754,067	0.001	0.031	0	1
Risk (L+M+H)	1,754,067	0.109	0.312	0	1
Distance to water (<100 m)	1,754,067	0.075	0.263	0	1
Panel C: Local authority characteristics					
Annual household income	324	42,745.470	8,270.216	32,338.461	57,644.445
Index of Multiple Deprivation	308	19.777	8.012	8.500	34.300
Age	308	42.144	5.094	33.300	50.500
Urban	330	0.727	0.446	0.000	1.000
Education level (%)	324	27.212	7.903	16.900	41.000
Votes for the Green Party (%)	316	2.970	2.007	0.000	5.637
Votes for Brexit (%)	330	54.504	9.963	32.540	68.860

Notes: This table provides descriptive statistics for the variables used in the empirical analysis. Summary statistics of property level variables are presented in Panel A. Panel B summarizes statistics of the measurements of flood risk. Summary statistics of local authorities level variables are shown in Panel C. (ln) denotes that a variable is measured in natural logarithm.

Table 2: Effect of flood events and Flood Re on property prices

	1	2	3	4	5
Dependent variable	D. Property price (ln)				
Flooded	-0.009**	-0.018***	-0.015***	-0.021***	-0.016***
	(-2.21)	(-3.14)	(-2.70)	(-3.39)	(-2.97)
Flooded x Post Flood Re		0.015**	0.014**	0.019**	0.018***
		(2.07)	(2.15)	(2.58)	(2.68)
Flash-flooded	0.002	0.001	0.004	0.000	0.004
	(0.34)	(0.09)	(0.57)	(0.01)	(0.49)
Flash-flooded x Post Flood Re		0.003	0.000	0.004	0.001
		(0.20)	(0.02)	(0.30)	(0.08)
3 dig plc X Year FE (current)	Yes	Yes	Yes	No	No
3 dig plc X Year FE (previous)	Yes	Yes	Yes	No	No
3 dig plc X Year FE (current) X Year FE (previous)	No	No	No	Yes	Yes
Built year FE	Yes	Yes	Yes	Yes	Yes
Property controls	No	No	Yes	No	Yes
Observations	1,754,067	1,754,067	1,754,067	1,754,067	1,754,067
R^2	0.761	0.761	0.766	0.788	0.792

Notes: Column 1 of this table presents estimation results of equation 2 without the interaction variable, Flood Risk × Post Flood Re. Column 2 and 3 of this table present estimation results of equation 2. Column 4 and 5 of this table presents estimation results of equation 3. Measurements of flood risk in this table is Flooded and Flash-flooded. The dependent variable in this table is D. Property price (ln) and property control variables include sets of dummy variables indicating property types, forms of tenure and whether the property is new built in the previous transaction. Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at local authority district level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Placebo tests

Panel A (Placebo test: Extension of the SoP in July 2013)	1	2	3	4
Dependent variable	D. Property price (ln)			
Flooded	-0.013**	-0.012**	-0.015**	-0.014**
	(-2.11)	(-1.97)	(-2.15)	(-2.01)
Flooded x Post SoP extension	-0.001	0.002	-0.001	0.003
	(-0.09)	(0.28)	(-0.10)	(0.30)
Flash-flooded	0.001	0.001	0.007	0.007
	(0.10)	(0.09)	(0.58)	(0.58)
Flash-flooded x Post SoP extension	0.002	0.006	-0.003	0.001
	(0.14)	(0.45)	(-0.22)	(0.09)
3 dig plc X Year FE (current)	Yes	Yes	No	No
3 dig plc X Year FE (previous)	Yes	Yes	No	No
3 dig plc X Year FE (current) X Year FE (previous)	No	No	Yes	Yes
Built year FE	Yes	Yes	Yes	Yes
Property controls	No	Yes	No	Yes
Observations	933,566	933,566	933,566	933,566
R^2	0.796	0.801	0.818	0.822

Panel B (Monte Carlo simulations for the role of flood and Flood Re)	1	2
Dependent variable	D. Property price (ln)	
Explanatory variable	Placebo-flooded	Placebo-flooded x Post Flood Re
Rejection rate at the 10% lelvel (2-tailed test)	13.60	11.40
Rejection rate at the 5% lelvel (2-tailed test)	7.30	7.40
Rejection rate at the 1% lelvel (2-tailed test)	2.60	1.80
Mean coefficient (t-statistics)	-0.002 (-0.50)	0.003(0.60)

Notes: Column 1 and 2 in Panel A of this table present estimation results of equation 2 with the placebo treatment (extension of the SoP). Column 3 and 4 of this table present estimation results of equation 3 with the placebo treatment (extension of the SoP). Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at local authority district level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Column 1 (2) of Panel B shows the rejection rates of the null hypothesis of the estimated coefficient of Placebo-flooded (Placebo-flooded x Post Flood Re)=0 at the 10%, 5%, and 1% levels, the mean coefficient and t-statistics of the two variables are also presented.

Table 4: Effect of Flood Re on property prices (Sample split-demographic characteristics)

	1	2	3	4	5	6	7	8	9	10
Dependent variable	D. Property price (ln)									
Sample split	Annual household income		Index of multiple deprivation		Age		Education		Urban/Rural area	
	$\geq p50$	$<p50$	$\geq p50$	$<p50$	$\geq p50$	$<p50$	$\geq p50$	$<p50$	Urban	Rural
Flooded	-0.024***	-0.001	-0.010*	-0.021***	-0.021**	-0.017**	-0.023***	-0.004	-0.022***	-0.003
	(-3.44)	(-0.12)	(-1.76)	(-2.99)	(-2.57)	(-2.37)	(-3.14)	(-0.56)	(-3.54)	(-0.36)
Flooded x Post Flood Re	0.019**	0.007	0.004	0.027***	0.029***	0.009	0.023**	0.008	0.022**	0.008
	(2.38)	(0.70)	(0.43)	(3.46)	(3.29)	(0.78)	(2.47)	(0.88)	(2.57)	(0.91)
Flash-flooded	0.024*	-0.004	-0.001	0.014	0.009	-0.005	0.007	0.005	0.002	0.005
	(1.91)	(-0.43)	(-0.12)	(1.22)	(0.88)	(-0.36)	(0.67)	(0.41)	(0.14)	(0.56)
Flash-flooded x Post Flood Re	-0.015	0.007	0.000	0.002	0.002	-0.002	0.000	-0.004	-0.000	0.010
	(-0.83)	(0.39)	(0.02)	(0.11)	(0.14)	(-0.07)	(0.01)	(-0.19)	(-0.02)	(0.53)
3 dig plc X Year FE (current) X Year FE (previous)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Built year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chow test F-statistics	2.44		2.71		2.85		1.21		3.50	
Observations	878,670	842,721	880,974	790,351	742,261	928,234	882,770	835,253	1,330,189	413,634
R^2	0.796	0.790	0.788	0.801	0.791	0.795	0.795	0.793	0.793	0.795

Notes: This table presents estimation results of equation 3 based on different sub-samples. Sample in column 1 (2) includes property transactions in local authority districts with higher (lower) average annual income. Sample in column 3 (4) includes property transactions in local authority districts with higher (lower) Index of multiple deprivation. Sample in column 5 (6) includes property transactions in local authority districts with higher (lower) age. Sample in column 7 (8) includes property transactions in local authority districts with higher (lower) education level. Sample in column 9 (10) includes property transactions in local authority districts in urban (rural) area. Measurements of flood risk in this table is Flooded and Flash-flooded. The dependent variable in this table is D. Property price (ln) and property control variables include sets of dummy variables indicating property types, forms of tenure and whether the property is new built in the previous transaction. Definitions of variables are detailed in Table A.1 in the appendix. The Chow test F-statistic is the F-statistic from a Chow test for equality of the estimated coefficients between the two respective sub-samples. Standard errors are clustered at local authority district level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Effect of Flood Re on property prices (Sample split-revealed believes)

	1	2	3	4
Dependent variable	D. Property price (ln)			
Sample split	Percentage of vote for the Green Party		Percentage of vote for Brexit	
	$\geq p50$	$<p50$	$\geq p50$	$<p50$
Flooded	-0.016*	-0.017***	-0.007	-0.022***
	(-1.80)	(-2.75)	(-0.84)	(-2.99)
Flooded x Post Flood Re	0.016	0.020**	0.012	0.022**
	(1.30)	(2.41)	(1.07)	(2.37)
Flash-flooded	-0.005	0.016	0.004	0.004
	(-0.43)	(1.42)	(0.36)	(0.36)
Flash-flooded x Post Flood Re	0.012	-0.012	-0.002	0.003
	(0.59)	(-0.70)	(-0.10)	(0.22)
Chow test F-statistics	0.50		1.15	
3 dig plc X Year FE (current)	Yes	Yes	Yes	Yes
Built year FE	Yes	Yes	Yes	Yes
Property controls	Yes	Yes	Yes	Yes
Observations	889,755	850,770	782,499	961,677
R^2	0.798	0.791	0.796	0.791

Notes: This table presents estimation results of equation 3 based on different sub-samples. Sample in column 1 (2) includes property transactions in local authority districts with higher (lower) percentage of vote for the Green Party. Sample in column 3 (4) includes property transactions in local authority districts with higher (lower) percentage of vote for Brexit. Measurements of flood risk in this table is Flooded and Flash-flooded. The dependent variable in this table is D. Property price (ln) and property control variables include sets of dummy variables indicating property types, forms of tenure and whether the property is new built in the previous transaction. Definitions of variables are detailed in Table A.1 in the appendix. The Chow test F-statistic is the F-statistic from a Chow test for equality of the estimated coefficients between the two respective sub-samples. Standard errors are clustered at local authority district level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Effect of Flood Re on property prices- Alternative measurements of flood risk

Panel A	1	2	3	4
Dependent variable	D. Property price (ln)			
Risk (L+M+H)	-0.006***	-0.004***	-0.006***	-0.004***
	(-4.83)	(-3.24)	(-4.56)	(-3.11)
Risk (L+M+H) x Post Flood Re	0.005***	0.004***	0.004***	0.004***
	(3.74)	(3.67)	(3.55)	(3.45)
3 dig plc X Year FE (current)	Yes	Yes	No	No
3 dig plc X Year FE (previous)	Yes	Yes	No	No
3 dig plc X Year FE (current) X Year FE (previous)	No	No	Yes	Yes
Built year FE	Yes	Yes	Yes	Yes
Property controls	No	Yes	No	Yes
Observations	1,754,067	1,754,067	1,754,067	1,754,067
R^2	0.761	0.766	0.788	0.792
Panel B	1	2	3	4
Distance to water (<100m)	-0.012***	-0.008***	-0.013***	-0.008***
	(-11.04)	(-7.17)	(-10.49)	(-7.04)
Distance to water (<100m) x Post Flood Re	0.005***	0.004***	0.005***	0.005***
	(4.31)	(3.99)	(4.46)	(4.08)
3 dig plc X Year FE (current)	Yes	Yes	No	No
3 dig plc X Year FE (previous)	Yes	Yes	No	No
3 dig plc X Year FE (current) X Year FE (previous)	No	No	Yes	Yes
Built year FE	Yes	Yes	Yes	Yes
Property controls	No	Yes	No	Yes
Observations	1,754,067	1,754,067	1,754,067	1,754,067
R^2	0.761	0.766	0.788	0.792

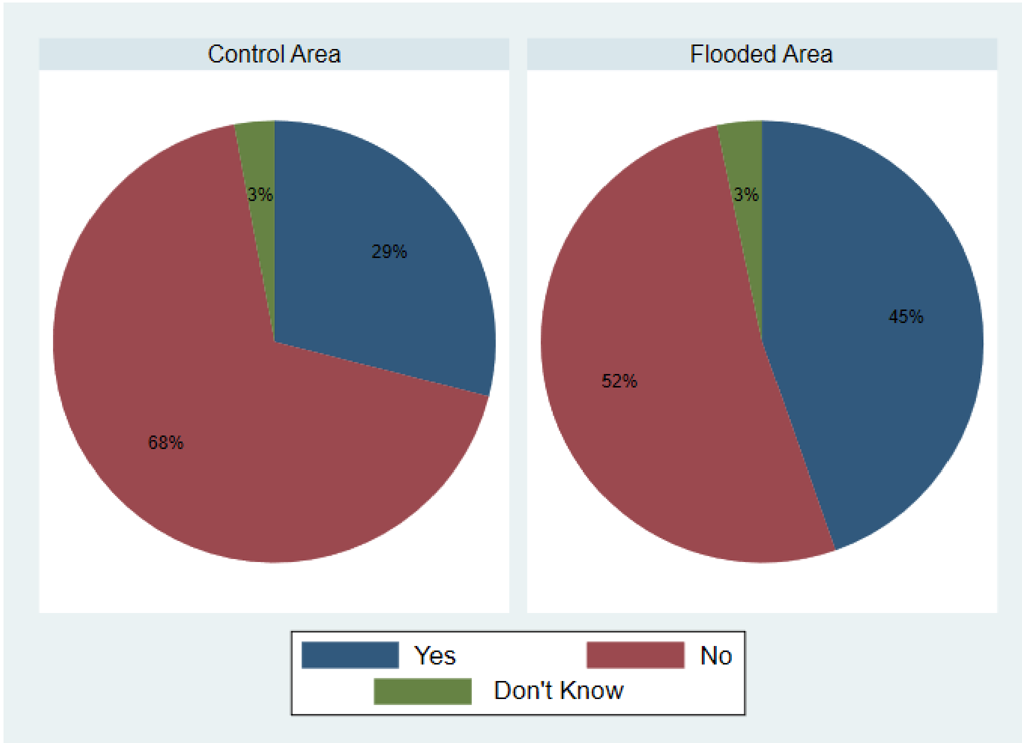
Notes: Column 1 and 2 of this table presents estimation results of equation 2. Column 3 and 4 of this table presents estimation results of equation 3. Measurement of flood risk is Risk (L+M+H) in Panel A and Distance to water (<100m) in Panel B. The dependent variable in this table is D. Property price (ln) and property control variables include sets of dummy variables indicating property types, forms of tenure and whether the property is new built in the previous transaction. Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at local authority district level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Effect of flood events and Flood Re on transaction volume

	1	2	3
Dependent variable		Trade	
Flooded	-0.005**	-0.036***	-0.036***
	(-2.17)	(-9.81)	(-9.97)
Flooded x Post Flood Re		0.061***	0.060***
		(9.69)	(9.69)
Flash-flooded	0.003	-0.001	-0.002
	(0.81)	(-0.15)	(-0.25)
Flash-flooded x Post Flood Re		0.008	0.008
		(0.87)	(0.85)
3 dig plc X Year FE	Yes	Yes	Yes
Built year FE	Yes	Yes	Yes
Property controls	No	No	Yes
Observations	14,446,899	14,446,899	14,446,899
R^2	0.014	0.014	0.014

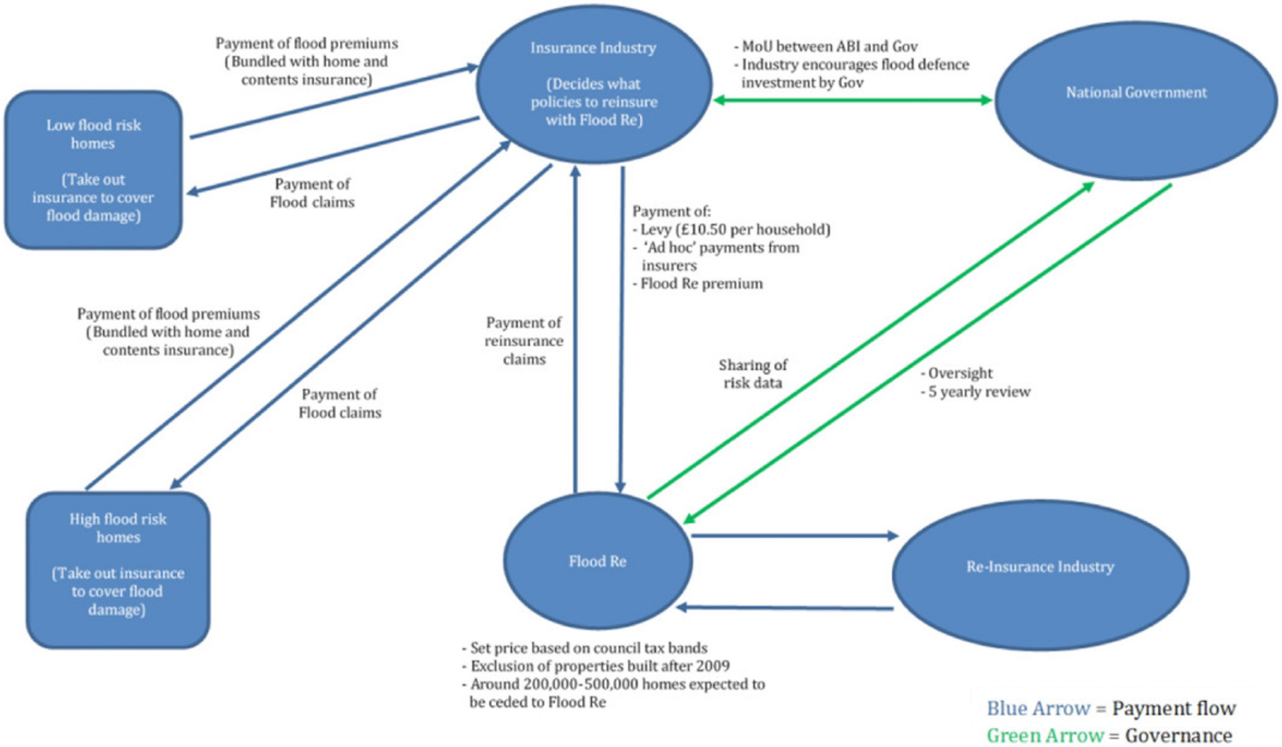
Notes: Column 1 of this table presents estimation results of equation 4 without the interaction terms, Flooded $\times$ Post Flood Re and Flash-flooded $\times$ Post Flood Re. Column 2 and 3 of this table presents estimation results of equation 4. The dependent variable in this table is a dummy variable indicates whether the property is traded in the year of observation. Property control variables include sets of dummy variables indicating property types, forms of tenure and whether the property is new built in the previous transaction. Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at local authority district level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 1: Awareness of Flood Re



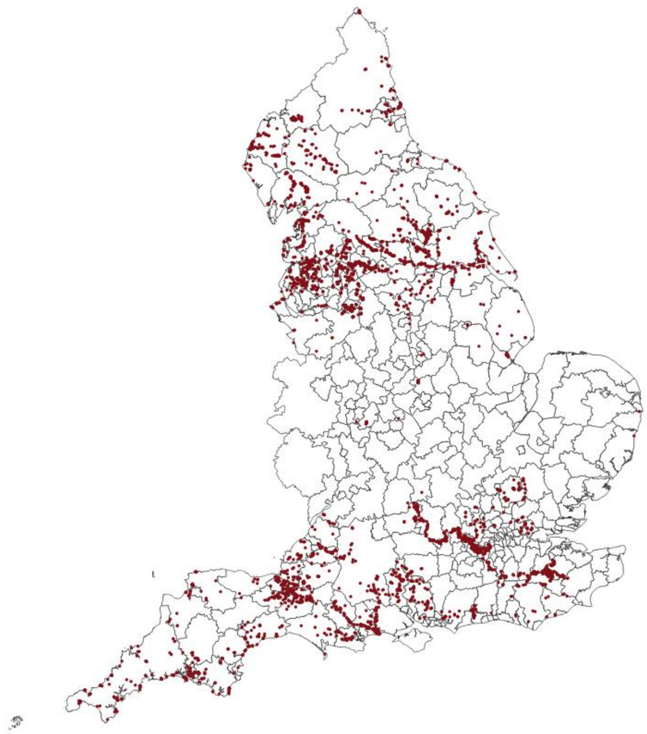
Notes: This figure shows the awareness of Flood Re in flooded area and non-flooded area. The data is based on the survey data of the 2018 Availability and Affordability of Insurance report.

Figure 2: Flood Re mechanism



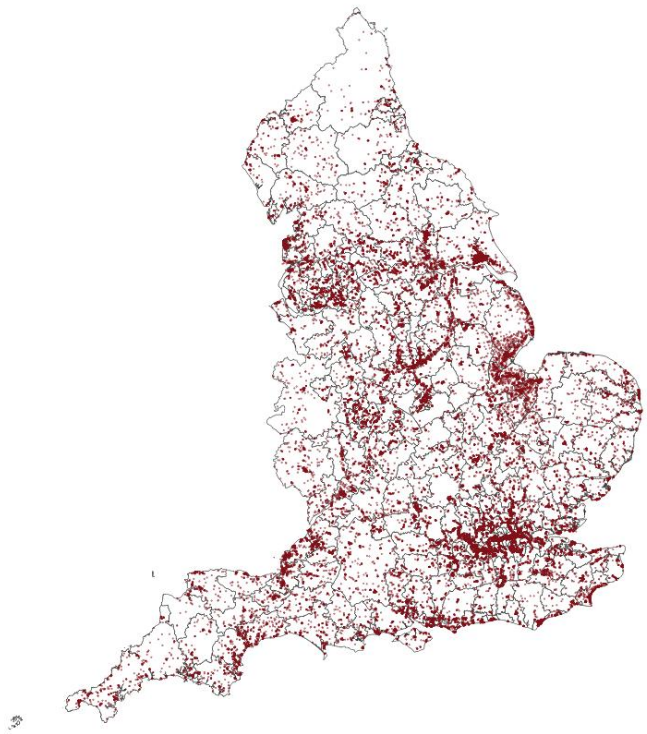
Notes: This figure was produced in Crick et al. (2018), depicting the mechanism of Flood Re and the interplay between different key players of Flood Re.

Figure 3: Map of flooded 6-digit postcodes



Notes: This figure depicts the 6-digit postcodes of properties experiencing at least one flood event lasting for more than a day in the past four years of transactions.

Figure 4: Map of 6-digit postcodes with above no/very low flood risk

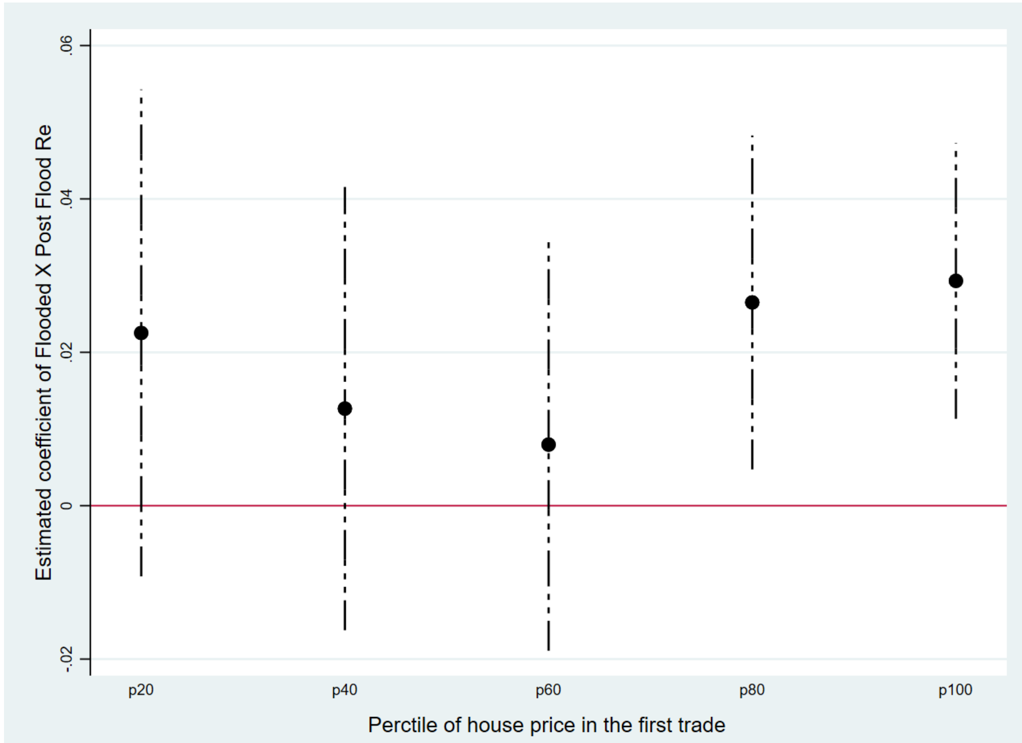


Notes: This figure depicts the 6-digit postcodes of properties at flood risk.

Figure 5: Map of 6-digit postcodes within 100 meters to river/sea

Notes: This figure depicts the 6-digit postcodes of properties within 100 meters to river/sea.

Figure 6: Effect of Flood Re at different percentiles of the property prices distribution



Notes: Each point in the figure represents the estimated coefficient of Flooded x Post Flood Re of a specific percentile of the property prices (in the first transaction) distribution and each dash line represents the 95% confidence interval of each estimated coefficient. The specification of the estimations follows the specification in column 5 of Table 2.

8 Appendix

Table A.1: Variable definitions

Variable	Definition	Source
Property price (ln)	Natural logarithm of property price.	HM Land Registry Price Paid Data
D. Property price (ln)	First difference of the natural logarithm of property price.	HM Land Registry Price Paid Data
New built	A dummy variable=1 if the property is newly built in the previous transaction, 0 otherwise.	HM Land Registry Price Paid Data
Detached	A dummy variable=1 if the property is a detached house, 0 otherwise.	HM Land Registry Price Paid Data
Semi-detached	A dummy variable=1 if the property is a semi-detached house, 0 otherwise.	HM Land Registry Price Paid Data
Terraced	A dummy variable=1 if the property is a terraced house, 0 otherwise.	HM Land Registry Price Paid Data
Flat	A dummy variable=1 if the property is a flat, 0 otherwise.	HM Land Registry Price Paid Data
Other	A dummy variable=1 if the property is other property type, 0 otherwise.	HM Land Registry Price Paid Data
Freehold	A dummy variable=1 if the legal ownership of property is freehold, 0 otherwise.	HM Land Registry Price Paid Data
Leasehold	A dummy variable=1 if the legal ownership of property is leasehold, 0 otherwise.	HM Land Registry Price Paid Data
Trade	A dummy variable=1 if the property is transacted in the year of observation, 0 otherwise.	HM Land Registry Price Paid Data
Flooded	A dummy variable=1 if the property only experiences flood event last for more than a day four years before the transaction, 0 otherwise.	EA Recorded Flood Outlines
Flash-flooded	A dummy variable=1 if the property only experiences flood event last for a day four years before the transaction, 0 otherwise.	EA Recorded Flood Outlines
Risk (L+M+H)	A dummy variable=1 if the property is in a 6-digit postcode classified as at least low risk, 0 otherwise.	EA Flood Map
Distance to water (<100 m)	A dummy variable=1 if the property is within 100 meters of river or sea, 0 otherwise.	Authors' calculation
Annual household income	Average annual household income of local authority district in 2019.	Office of National Statistics
Index of multiple deprivation	Index of multiple deprivation of local authority district in 2019.	Office of National Statistics
Age	Average age of the households per local authority district in 2019.	Office of National Statistics
Education	Proportion of population with level 4 or above qualification (e.g. degree with honours and postgraduate certificate) in local authority district in 2019.	Office of National Statistics
Urban	A dummy variable=1 if the local authority district is urban area, 0 otherwise.	Office of National Statistics
Percentage of votes for the Green Party	Percentage of votes for the Green Party in the 2019 United Kingdom general election of local authority district.	House of Common
Percentage of votes for Brexit	Percentage of votes for Brexit per local authority district.	Data.gov.uk

Table A.2: Correlation of local authority variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Annual household income	1						
(2) Index of multiple deprivation	-0.699	1					
(3) Age	-0.02	-0.446	1				
(4) Education level	0.757	-0.514	-0.148	1			
(5) Urban	0.001	0.304	-0.582	-0.007	1		
(6) Percentage of votes for the Green Party	0.055	-0.077	-0.022	0.189	-0.063	1	
(7) Percentage of votes for Brexit	-0.534	0.213	0.394	-0.889	-0.129	-0.251	1

Notes: This table shows the correlation matrix of local authority variables.

Table A.3: Awareness of Flood Re

	1	2
Dependent variable	Awareness of Flood Re	
Flooded	0.154**	-0.340*
	3.23	-2.14
Flooded x Age:		
35-54		0.361*
		(2.11)
>55		0.455**
		(2.89)
Flooded x Income level:		
26,000-41,599		-0.053
		(-0.39)
>41,600		0.163
		(1.25)
Flooded x Tax band:		
C-D		0.023
		(0.17)
E-H		0.019
		(0.11)
Age:		
35-54		-0.303
		(-1.79)
>55		-0.275
		(-1.49)
Income level:		
26,000-41,599		0.110
		(0.90)
>41,600		-0.021
		(-0.16)
Tax band:		
C-D		-0.048
		(-0.46)
E-H		-0.091
		(-0.85)
Observations	772	455
R^2	0.020	0.041

Notes: This table shows the heterogeneity in the awareness of Flood Re among the respondents in the survey of the 2018 Availability and Affordability of Insurance report. The dependent variable in this table is a dummy variable indicating whether the respondent is aware of Flood Re. Standard errors are clustered at region level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.4: Effect of Flood Re on property price (Sample split-demographic characteristics with the *ex-ante* flood risk measurement)

	1	2	3	4	5	6	7	8	9	10
Dependent variable	D. Property price (ln)									
Sample split	Annual household income		Index of multiple deprivation		Age		Education		Urban/Rural area	
	$\geq p50$	$<p50$	$\geq p50$	$<p50$	$\geq p50$	$<p50$	$\geq p50$	$<p50$	Urban	Rural
Risk (L+M+H)	-0.005***	-0.001	-0.003	-0.005***	-0.002	-0.006***	-0.006***	-0.001	-0.006***	0.000
	(-3.50)	(-0.54)	(-1.40)	(-3.01)	(-1.17)	(-3.52)	(-3.46)	(-0.66)	(-4.14)	(0.08)
Risk (L+M+H) x Post Flood Re	0.007***	0.001	0.003	0.006***	0.003	0.007***	0.007***	0.001	0.006***	0.001
	(4.07)	(0.47)	(1.46)	(3.50)	(1.37)	(3.91)	(4.23)	(0.62)	(4.27)	(0.39)
3 dig plc X Year FE (current) X Year FE (previous)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Built year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Chow test F-statistics	2.41		3.24		4.49		2.29		6.65	
Observations	878,670	842,721	880,974	790,351	742,261	928,234	882,770	835,253	1,330,189	413,634
R^2	0.796	0.790	0.788	0.801	0.791	0.795	0.795	0.793	0.793	0.795

Notes: This table presents estimation results of equation 3 based on different sub-samples. Sample in column 1 (2) includes property transactions in local authority districts with higher (lower) average annual income. Sample in column 3 (4) includes property transactions in local authority districts with higher (lower) Index of multiple deprivation. Sample in column 5 (6) includes property transactions in local authority districts with higher (lower) age. Sample in column 7 (8) includes property transactions in local authority districts with higher (lower) education level. Sample in column 9 (10) includes property transactions in local authority districts in urban (rural) area. Measurements of flood risk in this table is Risk (L+M+H). The dependent variable in this table is D. Property price (ln) and property control variables include sets of dummy variables indicating property types, forms of tenure and whether the property is new built in the previous transaction. Definitions of variables are detailed in Table A.1 in the appendix. The Chow test F-statistic is the F-statistic from a Chow test for equality of the estimated coefficients between the two respective sub-samples. Standard errors are clustered at local authority district level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.5: Effect of Flood Re on property price (Sample split-revealed believes with the *ex-ante* flood risk measurement)

	1	2	3	4
Dependent variable	D. Property price (ln)			
Sample split	Percentage of vote for the Green Party		Percentage of vote for Brexit	
	$\geq p50$	$<p50$	$\geq p50$	$<p50$
Risk (L+M+H)	-0.004**	-0.004***	-0.002	-0.006***
	(-2.13)	(-2.64)	(-0.93)	(-3.38)
Risk (L+M+H) x Post Flood Re	0.006***	0.003**	0.003	0.006***
	(2.91)	(2.14)	(1.43)	(3.60)
Chow test F-statistics	0.37		2.34	
3 dig plc X Year FE (current)	Yes	Yes	Yes	Yes
Built year FE	Yes	Yes	Yes	Yes
Property controls	Yes	Yes	Yes	Yes
Observations	889,755	850,770	782,499	961,677
R^2	0.798	0.791	0.796	0.791

Notes: This table presents estimation results of equation 3 based on different sub-samples. Sample in column 1 (2) includes property transactions in local authority districts with higher (lower) percentage of vote for the Green Party. Sample in column 3 (4) includes property transactions in local authority districts with higher (lower) percentage of vote for Brexit. Measurements of flood risk in this table is Risk (L+M+H). The dependent variable in this table is D. Property price (ln) and property control variables include sets of dummy variables indicating property types, forms of tenure and whether the property is new built in the previous transaction. Definitions of variables are detailed in Table A.1 in the appendix. The Chow test F-statistic is the F-statistic from a Chow test for equality of the estimated coefficients between the two respective sub-samples. Standard errors are clustered at local authority district level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.6: Effect of Flood Re on property prices-Continuous measurements of flood risk

Panel A	1	2	3	4
Dependent variable	D. Property price (ln)			
Flood duration (in 100 days)	-0.026***	-0.023***	-0.027***	-0.024**
	(-2.84)	(-2.82)	(-2.61)	(-2.59)
Flood duration x Post Flood Re	0.018	0.020*	0.021*	0.023**
	(1.62)	(1.90)	(1.76)	(2.04)
3 dig plc X Year FE (current)	Yes	Yes	No	No
3 dig plc X Year FE (previous)	Yes	Yes	No	No
3 dig plc X Year FE (current) X Year FE (previous)	No	No	Yes	Yes
Built year FE	Yes	Yes	Yes	Yes
Property controls	No	Yes	No	Yes
Observations	1,754,067	1,754,067	1,754,067	1,754,067
R^2	0.761	0.766	0.788	0.792
Panel B	1	2	3	4
Dependent variable	D. Property price (ln)			
Flood risk mid-point	-0.002***	-0.001**	-0.002***	-0.001**
	(-3.95)	(-2.50)	(-3.78)	(-2.45)
Flood risk mid-point x Post Flood Re	0.002***	0.001***	0.002***	0.002***
	(2.98)	(2.82)	(2.78)	(2.61)
3 dig plc X Year FE (current)	Yes	Yes	No	No
3 dig plc X Year FE (previous)	Yes	Yes	No	No
3 dig plc X Year FE (current) X Year FE (previous)	No	No	Yes	Yes
Built year FE	Yes	Yes	Yes	Yes
Property controls	No	Yes	No	Yes
Observations	1,754,067	1,754,067	1,754,067	1,754,067
R^2	0.761	0.766	0.788	0.792
Panel C	1	2	3	4
Dependent variable	D. Property price (ln)			
Distance to water (in 1000 meters)	-0.003***	-0.005***	-0.002***	-0.005***
	(-4.31)	(-7.13)	(-3.49)	(-6.28)
Distance to water x Post Flood Re	0.009***	0.008***	0.008***	0.008***
	(13.24)	(12.42)	(12.24)	(11.49)
3 dig plc X Year FE (current)	Yes	Yes	No	No
3 dig plc X Year FE (previous)	Yes	Yes	No	No
3 dig plc X Year FE (current) X Year FE (previous)	No	No	Yes	Yes
Built year FE	Yes	Yes	Yes	Yes
Property controls	No	Yes	No	Yes
Observations	1,754,067	1,754,067	1,754,067	1,754,067
R^2	0.761	0.766	0.788	0.792

Notes: Column 1 and 2 of this table presents estimation results of equation 2. Column 3 and 4 of this table presents estimation results of equation 3. The continuous measurement of flood risk are Flood duration (in 100 days) in Panel A, Flood risk mid-point in Panel B and Distance to water (in 1,000 meters) in Panel C. The dependent variable in this table is D. Property price (ln) and property control variables include sets of dummy variables indicating property types, forms of tenure and whether the property is new built in the previous transaction. Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at local authority district level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.7: Effect of flood events and Flood Re on days since last trade

	1	2	3
Dependent variable	Days since last trade (ln)		
Flooded	0.006***	0.076***	0.076***
	(3.47)	(19.96)	(19.92)
Flooded x Post Flood Re		-0.131***	-0.131***
		(-13.46)	(-13.43)
Flash-flooded	0.006**	0.070***	0.070***
	(2.09)	(13.18)	(13.27)
Flash-flooded x Post Flood Re		-0.115***	-0.115***
		(-9.24)	(-9.26)
3 dig plc X Year FE (current)	Yes	Yes	No
3 dig plc X Year FE (previous)	Yes	Yes	No
3 dig plc X Year FE (current) X Year FE (previous)	No	No	Yes
Built year FE	Yes	Yes	Yes
Property controls	Yes	Yes	Yes
Observations	1,754,067	1,754,067	1,754,067
R^2	0.939	0.939	0.939

Notes: Column 1 and 2 of this table present estimation results of equation 2 with the dependent variable measuring the natural logarithm of the number of days since the last transaction, column 1 present estimation results without the interaction term, Flooded × Post Flood Re and Flash-flooded × Post Flood Re. Column 3 of this table presents estimation results of equation 3 with the dependent variable measuring the natural logarithm of the number of days since the last transaction. Measurements of flood risk in this table is Flooded and Flash-flooded. The dependent variable in this table is D. Property price (ln) and property control variables include sets of dummy variables indicating property types, forms of tenure and whether the property is new built in the previous transaction. Definitions of variables are detailed in Table A.1 in the appendix. Standard errors are clustered at local authority district level and the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively