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High water, no marks? Biased lending after extreme weather

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Abstract

Policymakers have put forward proposals to ensure that banks do not underestimate long-term risks from climate change. To examine how lenders account for extreme weather, we compare matched repeat mortgage and property transactions around a severe flood event in England in 2013–14. First, lender valuations do not 'mark-to-market' against local price declines. As a result valuations are biased upwards. Second, lenders do not offset this valuation bias by adjusting interest rates or loan amounts. Third, borrowers with low credit risk self-select into high flood risk areas. Overall, these results suggest that lenders do not track closely the impact of extreme weather *ex-post*, and that public flood insurance programs may subsidise high income households.

Key words: Climate, flooding, house prices, mortgages.

JEL classification: D12, G21, Q51, Q54.

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1 Introduction

Properties across the world are exposed to long-term risks of extreme weather events such as hurricanes, flooding and fires. Sudden readjustments in the value of housing collateral can lead to swings in household borrowing and consumption (Campbell and Cocco, 2007; Mian and Sufi, 2011; Keys et al., 2012; Greenwald, 2018). Academics and policymakers are increasingly concerned that financial institutions may be underestimating their exposure to climate-related risks, but evaluating their behaviour often requires assumptions about uncertain climate change scenarios. (Daniel et al., 2016; Farid et al., 2016; Battiston et al., 2017; Batten et al., 2018; Dafermos et al., 2018).

This paper exploits a severe flood event to examine how lenders adjust their valuation of housing collateral using *available* market information. By focusing on an actual event, rather than scenarios, we set a low bar for how lenders take climate-related risks into account. First, we compare changes in lenders' valuations (used for mortgage refinancing) against changes in sales prices for actual property transactions. If lenders "mark-to-market", using locally available price information, valuations should change in line with transaction prices. Instead, we find that valuations do not adjust to price declines in neighborhoods that experience prolonged flooding, and valuations are, as a result, biased upwards. Second, we would expect lower house prices to be associated with increasing interest rates and lower loan amounts in refinancing transactions, to compensate for higher leverage (loan-to-value ratio) and credit risk. But valuations do not change after prolonged flooding, and loan amounts are unaffected. Lenders may however adjust to flooding via interest rates, which increase slightly, but this result is not robust to controls for differential trends between low- and high-risk mortgages. Third, increases in flood risk indicators do not appear to lead to a fall in property prices.

Finally, we provide evidence of selection of low credit risk borrowers into high flood risk areas. Borrowers living closer to water have relatively higher income and display lower loan-to-value ratios than borrowers living farther away. They buy more expensive properties, which is consistent with amenity valuation of living closer to the water.

The analysis focuses on the effect of a severe flooding event in England that caused over £1.3 billion in damages. Our strategy to identify bias in lender valuations of housing collateral is based on Agarwal et al. (2015). We estimate the decrease in property prices following prolonged flooding, and we then test whether valuations (for mortgage refinancing) in the same geographic area change similarly. Strong contractual incentives mean that refinancing decisions around set dates can be taken as quasi-exogenous. UK borrowers typically refinance at the end of the two- to five-year introductory rate period to avoid higher interest rates (Cloyne et al., 2019).

In the winter of 2013-14, regions in the Thames catchment area and the east coast of England were hit by a combination of inland (river and surface) and coastal floods. In February 2014, the Environment Agency (EA) released a major update of its flood maps, which are publicly available. We construct a dataset comprising 119,239 properties that are transacted (resold or refinanced) at least twice in a six-year window before and after the winter floods of 2013-14 (WF1314). For 38,747 mortgage refinancing transactions we have detailed information on borrower and loan characteristics, including the house valuation used by the lender, the loan amount, and the interest rate. We combine this with postcode unit-level maps on flood outlines and flood risk (a postcode unit contains on average sixteen properties). To mitigate uncertainty about how economic agents absorb information on flood risk we use both actual flooding and changes in two independent sources of flood risk indicators (Browne and Hoyt, 2000; Siegrist and Gutscher, 2006; Eisensee and Strömberg, 2007; Brock and Hansen, 2017; Gibson et al., 2018). In the UK, flood insurance is provided by the private sector, and to proxy changes in the actuarial price of flood insurance, we also include Matrix Scores provided by JBA Risk Management (JBA) that are used by the majority of UK insurers.

Our identification relies on a comparison of property appreciation rates across two dimensions: flooded versus non-flooded, and sales prices versus valuations for mortgage refinancing. Both dimensions can be taken as quasi-exogenous. As mentioned above, UK mortgages tend to be refinanced when the introductory rate period expires, typically after two to five years, and negative interest rate shocks are not necessary to make refinancing attractive (Andersen et al., 2015; Keys et al., 2016). We use exogenous variation from a natural event, addressing concerns that house prices and borrowing may be jointly determined by unobserved shocks (Rosenzweig and Wolpin, 2000; Mian and Sufi, 2011). To capture variation in flood (risk) experience we define three treatment groups at postcode-unit level: long floods (50 days or more); short floods (less than 50 days); and risk increases (but not flooded). We compare the treatment groups to a control group of unaffected properties that experience neither flooding nor risk increases. We also create similar groups using the JBA Matrix Scores used by insurers.

We take several steps to address remaining concerns of sample selection both in the pre- and post-flood periods. First, we use propensity score matching to re-balance the control groups and increase comparability with observations in the treatment groups. Local terrain and weather can affect local demography and house prices. Natural amenities (Costanza et al., 1997; Earnhart, 2001; Bin et al., 2008a,b) and limited housing supply due to geographic constraints (Saiz, 2010) can increase the value of housing close to rivers and coast. Natural disasters can change the local demographics of affected areas if higher income households are more likely to purchase properties in disrupted areas (Liao and Panassié, 2018). We find that in our full sample, before matching, borrowers exposed to flooding tend to be higher income and lower risk.

Second, our methodology exploits repeat transactions to compare, across groups, *within* unit (property or mortgage) time variation in property transactions and lender valuations. To restrict the geographic scope of the analysis, and control for time-varying local house price trends, we add fixed effects at the postcode district level (each postcode district contains on average about 6,000 properties within our sample). We interact them with year fixed effects to control for all time-variant conditions that affect properties in a district in the same way.[1] Our approach is similar to the literature that employs matched difference-in-difference estimators (Blundell et al., 2004; Gropp et al., 2016).

We use changes in the prices of actual property transactions as a benchmark against which to measure bias in bank valuations. Our main focus is on the effect of flood and flood risk on "valuation bias", the relative change of valuations used for refinancing against sales prices. This requires identifying the effect of flood (risk) on sales prices, but we do not seek to fully disentangle the different channels through which flood (risk) can affect property prices.[2]

Relative to unaffected properties in the same district, properties in postcode units that experience prolonged flooding see significant decreases in sales prices between -4.2% and -2.6% (using full and matched samples, respectively), but these are not reflected in valuations for mortgage refinancing. We estimate a positive valuation bias between 2.9% and 3.2% —almost perfectly offsetting the decline in sales prices. In other words, valuations for refinancing for flooded properties are roughly aligned with sales prices of *non-flooded* properties in the same area.

We find no significant effect of shorter flooding on sales prices—and no valuation bias. Surprisingly, increases in flood risk lead to a small increase in sales price (1% to 1.8%), which is offset by a small negative valuation bias (-1.2% to -1.3%).

The fall in collateral value should result in an increase in the loan-to-value ratio, which, in the UK, is the most important factor for mortgage rates and amounts (Best et al., 2020). We would expect decreases in property prices to be reflected in valuations, and result in higher interest rates and/or lower loan amounts for refinancing transactions. But since refinancing valuations appear to be unaffected by flooding or increases in flood risk, the effects on mortgage rates and loan amounts are limited. We find that lenders slightly adjust interest rates (but not amounts) for prolonged flooding, but this result is not robust to controls for

[1]This allows us to account for possible differences in appreciation due to the timing of the transactions and the specific local area.

[2]These include insurance premiums, planning constraints, local income, building quality. See Beltrán et al. (2018) for a meta-analysis of studies on the effect of flood risk on house prices.

differential trends between low- and high-risk mortgages.

Our results add to the growing literature on the effect of natural disasters on bank lending. We highlight how the house valuation channel, empirically tested by Ben-David (2011) and Agarwal et al. (2015) in the context of the pre-crisis housing boom, can be adapted to extreme weather events. Ben-David (2011) finds that during the pre-crisis housing boom, inflated transaction prices helped home buyers with insufficient down payments to draw larger mortgages. Agarwal et al. (2015) focus on refinancing transactions, and also find that the valuation bias is stronger when borrowers are highly leveraged. Our empirical approach is similar, but we look at a different question: how an exogenous flood shock changes valuations relative to sales prices.

Garmaise and Moskowitz (2009) and Chavaz (2016) find that negative effects from risk of natural disasters can be partially offset by specialist knowledge (available to local banks or insurers), and that this facilitates lending in areas vulnerable to natural disasters. Our results suggest that little local knowledge about flood risk is employed by lenders in valuing house prices following a flood, and that lenders instead rely on house prices indexes that do not capture variation in flooding within neighborhoods. Our result is more in line with de Greiff et al. (2018) who find that banks only recently started pricing climate risks in their corporate loans. They look at transition risks related to climate change policy, while we focus at physical risks from natural disasters.

The literature that exploits natural disasters to assess the reaction of banks to credit shocks does not take into account valuation as a separate channel. Valuation bias can lead to distortions in lending quantities by relaxing credit constraints. A substantial reduction in the value of the collateral available for refinancing could force marginal borrowers to pay higher rates, use savings to make up for the difference, or potentially default. Cortés and Strahan (2017) and Koetter et al. (forthcoming) find that (small) banks reallocate lending to areas affected by natural disasters. This channel may be supported by biased valuations of property collateral that prevent a tightening of credit constraints in affected areas. Biased collateral valuation can also sustain bank lending via their risk-based regulatory capital ratios, where collateral values are an important factor in setting regulatory requirements. Schüwer et al. (2019) find that, following Hurricane Katrina, banks with low capitalization managed their risk-based capital ratios by shifting their lending towards lower risk-weighted assets.[3]

We also find evidence that borrowers with low credit risk self-select into areas with high flood risk. This self-selection could limit the financial stability risks from a drop in house prices due to flooding. Using survey data, Bakkensen and Barrage (2017) find that selection into coastal homes is driven by both lower perceptions of flood risk and higher amenity values.[4] In their model, learning from flood shocks can lead to sharp drop in house prices. In turn, lenders can react to an exogenous reduction in collateral values by increasing interest rates and tightening credit limits (Cerqueiro et al., 2016). But Liao and Panassié (2018) find that households moving to areas affected by hurricanes tend to have higher income, which (all else equal) would lower credit risk. These households should be able to pay substantial insurance premiums, and withstand wealth and liquidity shocks caused by floods. The higher financial resources of households in flooded areas could also be the reason why, unlike Gallagher and Hartley (2017), we do not find any deleverage in flooded areas. This finding is relevant for evaluating public programs that subsidize flood insurance in high risk areas and are partly motivated by concerns about households' ability to secure mortgage financing (Anderson, 1974; Kriesel and Landry, 2004).

Surprisingly, we do not find that increases in flood risk are associated with lower property prices, in contrast with other research on climate risks. For example, Kousky (2010) finds that flooding causes a larger fall in house prices in floodplains, suggesting a reassessment of flood risk. Bernstein et al. (2019) find that properties exposed to the risk of rising sea levels sell for a discount. Our result may indicate that tighter planning in high flood risk areas push up prices, in line with the intuition in Saiz (2010), but additional data and research

[3]There is a more general debate on the role of fair value accounting, or mark-to-market, in the 2008 financial crisis. See Laux and Leuz (2010) for an overview.

[4]After hurricane Sandy, owners of expensive New Jersey coastal properties with views on Manhattan asked for a proposed flood wall to be built *behind* their properties to avoid losing the view on the skyline (?).

would be required to test this hypothesis.

Our results indicate that pricing of climate risks in mortgage lending has so far been limited. This may change in the near future if the use of automated valuation models (AVMs) becomes widespread among lenders. AVMs that exploit available granular data can reduce the bias in lender valuations (and the implicit cross-subsidy from non-flooded to flooded neighborhoods), but can also increase their volatility (Gallin et al., 2018; Bogin et al., 2019).

The remainder of the paper is structured as follows. Section 2 presents our setting and data, Section 3 describes our identification approach, and Section 4 discusses the main results. Section 5 concludes.

2 Setting and data

In this section we describe the winter floods of 2013-14 (WF1314) and the UK institutional setting for mortgage lending. We then set out how we create our dataset.

2.1 The winter floods of 2013-14

The WF1314 occurred between December 2013 and February 2014 and affected mainly two areas, the Thames river catchment and the East coast (Figure 1). Unusually, the WF13-14 featured a combination of flood types, including coastal and fluvial/groundwater/pluvial flooding (Huntingford et al., 2014). The River Thames catchment is the largest in the UK, and experienced the highest winter rainfall on record. The duration of high flows was exceptional, exceeding the high flow benchmark for 76 consecutive days, compared to the previous longest sequence of 30 days. In February 2014, the monthly river flow of the Thames was almost three times its long-term average. In December 2013, highest tidal surge since 1953 resulted in widespread coastal flooding.

The floods resulted in £1.3bn damage ($1.7bn at end-2013 exchange rate). As a comparison, property damage at the 99th percentile for US natural disasters is $0.5bn (Cortés and Strahan, 2017), but hurricanes Katrina (2005) and Harvey (2017) resulted in damages of over $125bn. In the UK, the 2007 floods resulted in damage of £3.9bn. The WF1314 were hence damaging, but not catastrophic. They were less extreme than recent US hurricanes studied in the literature, but arguably more representative of "'normal" flooding events.

2.2 Flood risk

Flood hazard maps estimate the probability and expected intensity of flooding in a geographic area.[5] In this paper, we use data from flood hazard maps produced by the Environment Agency (EA), a public body, and risk consultancy JBA Risk Management (JBA).[6]

Flood hazard maps are built starting from data on river flows, rain and sea level, which are used to estimate a hydrological model for flows, rainfalls and surge distributions within a given return period. These estimates are then combined with a digital terrain map to create a hydraulic model with flood extents and depths within each return period. The hydrological models use the terrain maps to define catchment areas and estimate peak flows, which are then turned into flood hazard maps. Updates in risk measures do *not* necessarily reflect changes in actual flood risk. Most of the changes are due to new terrain information and other modelling improvements.

EA flood hazard maps are publicly available and are used by local authorities for planning decision. About 9% of new residential development is constructed in flood risk areas, and the EA must be consulted on all planning applications. In 2016-17 the EA was consulted on about 2,400 projects, and in 530 cases it asked for modifications or refused permission (Defra, 2018). Solicitors and building surveyors in property transactions use EA maps to advise their clients on flood risk. EA maps are revised periodically, and the update in 2013-14 was particularly extensive. Flood risk probabilities increased for about 1,200 postcode units in our sample, and decreased for about 200 units.

[5] There are several types of tools available to assess flood risk. For example, catastrophe models are based on scenarios that take into account correlation of flood probabilities in different areas.

[6] The description in this section is based on discussions with JBA and the EA.

JBA is a private consultancy that develops flood hazard maps that are used by insurers to underwrite property policies. JBA estimate that they provide maps to 80% of UK insurers. JBA Matrix Scores combine flood probability and flood depth, taking into account flood defenses. The Matrix Scores are calculated for different return periods and for river, coastal and surface flooding separately. The return period with the highest score is retained, and scores for river, coastal flooding are then combined. Changes in JBA Matrix Scores can affect the technical (actuarial) price of flood insurance, but some insurers integrate the information into their own models, and actual premiums will differ from the actuarial price due to other business considerations. In this paper, we employ JBA Matrix Scores for 2013 and 2017.

Flood risk in the UK is typically covered by standard property insurance (Bennett and Edmonds, 2013). Since the 1960s, a series of gentlemen's agreements between industry and government have regulated the provision of flood insurance in high risk areas. These agreements became more formal in the early 2000s, following a series of floods and increased media attention (Escobar and Demeritt, 2014). In 2002, industry and government agreed on a "Statement of Principles" (SoP). Insurers committed to provide cover for properties exposed to flood risk; in exchange, the government increased its investment in flood defences. The SoP was revised in 2004 to exclude properties with flood probability above 1.3% (1 in 75 years) and properties built after 2008.

The SoP did not include a commitment to constrain the price of insurance. Improvements in flood hazard maps and more accurate risk-pricing threatened the informal cross-subsidy from low-risk to high-risk areas—even if survey evidence suggests that only flooded properties experienced significantly higher insurance premia (Defra, 2015). Starting in 2013, concerns about the affordability of flood insurance, and its implications for mortgage affordability, led to a review of the SoP. In 2016, the SoP was replaced by a flood reinsurance scheme, Flood Re, funded by an insurance levy. Under Flood Re, the reinsurance premium is fixed to the property's tax band.

2.3 The UK mortgage market

The most common mortgage products in the UK have an introductory period of two to five years during which the interest rate remains fixed. At the end of this period, the interest is reset at a higher rate, and borrowers have an incentive to refinance to avoid an increase in mortgage payments. For a typical two-year fixed rate product, the reset rate is about two percentage points higher than the introductory rate. Over 90% of borrowers choose a fixed rate product, and about 80% refinance their mortgage within one year of the expiration of the introductory deal (FCA, 2018). Cloyne et al. (2019) argue that these strong incentives mean that refinancing decisions can be taken as quasi-exogenous, limiting the room for self-selection. They exploit the exogenous refinancing time to estimate the effect of house prices on household borrowing, using mortgage refinancing data from the Product Sales Database. We follow their line of reasoning: borrowers with fixed-rate period mortgages have incentives to refinance at the end of the period. Conditional on their existing mortgage contract at the time of the WF1314, these incentives can be taken as exogenous.

Cloyne et al. (2019) exploit this feature to estimate the effect of house prices on household borrowing, and Benetton et al. (2018) use it to calculate counterfactual mortgage payments during the introductory period. Both papers use the Product Sales Database, which we also use in this paper.

The mortgage rate depends primarily on the loan-to-value (LTV) ratio, and increases with discrete jumps at LTV thresholds. Borrowers typically bunch just below the LTV threshold to benefit from the lower rate (Best et al., 2020), and negative shocks to house prices can cause substantial increases in interest rates at refinancing if the new deal falls into a higher LTV band. The other variables that affect loan pricing are borrower type (first-time buyer, home mover, remortgager) and rate type (length of fixed period). Borrower characteristics (income, age, credit score) do not affect pricing directly, but are used by lenders to approve or reject loan applications.

All borrowers must have property insurance in place in order to receive a loan, but lenders do not monitor insurance renewal. Substantial increases in insurance premium due to higher flood risk can affect mortgage availability, as lenders are required to consider committed expenditures such as insurance in their approval process.

For mortgages associated with a housing transaction, the buyer or the lender can ask for a surveyor report which then feeds into the house valuation process. However, in the vast majority of cases the valuation coincides with the transaction price. For refinancing transactions there is no linked property transaction. Lenders rely on the latest available transaction price of the property as well as an assessment of how the price might have evolved since the transaction, which is typically based on published house price indexes.

2.4 Constructing the dataset

In this section, we describe how we set up both the housing and the mortgage datasets, and how we merge them with information on flooding (and flood duration) and changes in flood risk measures (both from the EA as well as JBA) at postcode unit level. We restrict our analysis to the regions in the Thames catchment area and the east coast of England that were affected by the WF1314.

In our analyses, we compare property and mortgage characteristics in the three-year window before the WF1314 to the three-year window after this event. We identify property transactions in the pre-event period (November 2010 to October 2013), and retain those for which we can observe a second transaction in the post-event period (March 2014 to February 2017)).[7]

Property transactions. We use data from HM Land Registry, which covers the universe of UK property transactions since 1999. In the regions we consider, we can identify 2,849,650 properties in total. We construct the subsample of properties that are transacted both at least once in the three-year window before the WF1314 event period and at least once in the three year window after it. We use this panel of 80,492 properties to examine how sales prices change over time.

Mortgage transactions. We use FCA's Product Sales Database (PSD). In this data set,

[7] We describe individual steps of setting up the final dataset in the Online Appendix.

we observe new mortgages and mortgages refinanced with a new lender (“switchers") since 2005. We complement these data with the stock of mortgages outstanding in 2017 H1 to account for mortgages refinanced with the existing lender. Our sample consists of 2,218,607 mortgages. We then use this combined dataset to construct the subsample of refinanced mortgages, i.e. mortgages that are transacted both at least once in the three-year window before the WF1314 event period and at least once in the three year window after it. We exclude mortgage transaction pairs which begin with a refinancing transaction in the pre-event window as the associated property valuation might be biased. Using this panel of 38,747 mortgages, we examine how property valuations, loan amounts and mortgage rates change over time.

Flood outlines. Flood event data are provided by the Environment Agency as GIS layers. We map these layers to postcode units in order to match them with our property transactions and mortgage transactions datasets. The data include information on source of flooding (river, sea or other), the exact dates of the start and end of the flood, and the affected area of each flood outline. The majority of flood outlines during the WF1314 lasted for less than 2 months. Compared to all other flood events between 1995 and 2017, WF1314 were slightly longer on average. The majority of flood outlines during the WF1314 covered less than 10 km^2, a slightly wider area compared to other all flood events (1995-2017).

Flood hazard maps. EA flood maps start in 2008, and indicate the property-weighted average one-year ahead probability of floods per postcode unit. In our analyses, we exploit the major update of these maps which ocurred between 2013 and 2014. During this update, the number and definition of the risk categories changed.[8] In our analyses, we use the midpoint of the flood risk probability for each bucket. To ensure that we are are not capturing increases due to changes in the number of properties assessed per postcode unit, we focus on large increases in estimated flood risk of at least 0.8 percentage points.

[8]Between December 2008 and August 2013, flood probability was expressed in three categories: low (flood probability less than 0.5%), moderate (between 0.5% and 1.3%) and significant (greater than 1.3%). From 2014 the categories are four: very low (flood probability less than 0.1%), low (between 0.1% and 1%), medium (between 1% and 3.3%) and high (greater than 3.3%). See Online Appendix.

We complement these publicly available flood hazard maps with data from JBA. Our measure indicates the change in JBA Matrix Scores between 2013 and 2017 (at the postcode unit level).

3 Identification

In this section we describe our methodology, which combines a difference-in-difference analysis with a nearest neighbor propensity score matching approach.

3.1 Treatment groups

Extreme weather can affect property prices through different channels, including insurance premiums, local housing supply and the labor market. In this paper, we do not seek to disentangle the different channels, as we are mainly interested in comparing lenders' valuations with local transaction prices. We do however want to use a range of shocks to address uncertainty on how households absorb flood risk information. First, we use the public ex-ante measure of flood probability provided by the EA. This information is available to all house buyers, but they may pay limited attention. Households may pay more attention to insurance premiums. Our second ex-ante measure, from JBA, is available only to insurance firms, but it serves as a proxy for changes in insurers' technical price (i.e. the actuarially fair premium).

Actual flooding does not necessarily provide new information on flood risk if it is fully anticipated by existing risk measures. But severe floods such the WF1314 are rare, and it seems likely that they provide new information. Households' perceptions of flood risk may also readjust suddenly following actual flooding in their neighborhood. Compared to other floods, the distribution of flood duration for the WF1314 included several outlier postcode units that were flooded for more than 90 days. To capture possible non-linearities in the effect of flood duration on house prices, we consider separately properties with flood duration above/below the median length of 50 days.

Ex-post flooding is a less clean measure than ex-ante risk because damage to building structures, and renovation works, can change the quality of a property. This concern is partly mitigated by the fact that all mortgage borrowers must have flood insurance. Damaged properties are likely to be repaired, but only to (roughly) the state of the property prior to flooding.

To capture shocks related to flood (risk), we combine changes in EA flood probability and the flood outlines of the WF1314, and create the following three treatment groups:

1. *Flood (long)*: observations in postcode units that were flooded for 50 or more days.
2. *Flood (short)*: observations in postcode units that were flooded for up to 49 days.
3. *Risk up*: observations in postcodes units that were not flooded, but where the EA flood risk measure increased.[9]

The *Control* group includes all observations in postcode units that were neither affected by flooding nor by an increase in flood risk measurement. Similarly, we create treatment groups using the JBA flood risk measure.

The three treatment groups differ from the control group in terms of property and borrower characteristics. Table 1 Panel A reports descriptive statistics for property characteristics by treatment and control groups. Properties in the *Flood (long)* comparison group (column 1) have the shortest distance to water, the highest risk indicators, while the opposite is true for properties in the *Control* group (column 4). Compared to *Control* properties, those in both *Flood (long)* and *Flood (short)* are more expensive, while those in *Risk up* are cheaper.

Table 1 Panel B provides statistics for house buyers with a mortgage (which represent 69% of our sample, the balance are cash buyers), for whom we have information on personal

[9] As described in section 2 we consider only increases of at least 0.8 percentage points to ensure that the increase is genuine and not due to reclassification.

characteristics, such as income and age, and on mortgage details. Compared to *Control* borrowers, *Flood (long)*, *Flood (short)* borrowers have higher income and are older. Their properties are more expensive, they are less leveraged in terms of loan-to-value ratio (LTV) but not in terms of loan-to-income ratio (LTI). *Risk up* borrowers are much more similar to *Control* ones, eg. in terms of income, age, leverage and property values.

Panels C and D report average changes in sales prices and property valuations. Sales prices changed faster than valuations for refinancing across treatment and control groups. *Flood (long)* properties appreciated faster (both in sale price and valuation terms) than properties in the other groups. In Figure 2, we provide distributions of changes in both prices and house valuations around our event period for treatment and control groups. The distribution for valuations is narrower than that sales prices for all groups. The sales price and valuation distributions for flooded properties (Figure 2.b) are wider than for the other groups.

In summary, we observe substantial differences between treatment and control groups. In the next section, we explain how we apply propensity score matching to make our control observations more comparable to our treatment observations.

3.2 Control groups and propensity score matching

Table 1 suggests that there may be selection into the treatment groups, in particular for *Flood (long)* and *Flood (short)*. A likely factor that drives selection is distance to water, which is correlated with flood risk, but may also be correlated with unobservable characteristics such as amenities and employment opportunities in urban habitats close to rivers or the coast. Indeed, Table 1 suggests that properties in our three treatment groups are significantly closer to water than properties in our control group.

Price trends for properties with heterogeneous characteristics may diverge over time for reasons unrelated to flooding. Similarly, credit risk for borrowers with heterogenous characteristics is likely to diverge. This might invalidate the parallel trends assumption necessary to identify causal effects in difference-in-difference designs (Lechner, 2011).

To address this concern, we restrict our control group to observations that are most similar to those in the treatment groups. To do so, we conduct a propensity score matching procedure (Blundell et al., 2004; Bradley and Migali, 2012; Gropp et al., 2016) using the nearest neighbor algorithm (Abadie and Imbens, 2006, 2011). Given that the *Flood (short)* and *Flood (long)* treatment groups are similar, we combine them into one *Flood* group to simplify the matching. We conduct binary comparisons between treatment and control groups (Lechner, 2002). In the first step, we estimate the propensity of being assigned to *Flood* or *Risk Up* using logit models. In a second step, we use predicted propensity scores to find for each "treated" observation the ten most similar control observations.[10]

We report summary statistics for the *Matched Flood* and *Matched Risk Up* control samples in columns (5) and (6), respectively, in Table 1. Compared to the full sample in column (4), the matched samples are closer to water and have higher flood risk. In particular, the *Matched Flood* control sample in column (5) purchases more expensive properties, and borrows larger amounts against a higher income than the full control sample. As a result, the average loan-to-value and loan-to-income ratios are lower. Changes in property prices and valuations for refinancing are similar to the full control group. Overall, observations in the *Matched Flood* control group are more comparable to those in the treatment *Flood* counterpart group. The *Matched Risk Up* sample in column (6) is more similar to its treatment counterpart in terms of distance to water and risk indicators, but there are no large changes as the full sample was already relatively similar to the *Risk Up* treatment group.

3.3 Difference-in-difference estimation

To identify the differential effect (bias) on valuation for mortgage refinancing, relative to prices for actual housing transactions we follow Agarwal et al. (2015). The outcome variable is the change in value for the same property between two transactions. To capture the effect of flooding, the first transaction happens before the flood, and the second after. The first

[10]We provide the estimated coefficients of the corresponding logit models in the Online Appendix.

transaction in the pre-flood period is always a sale. Using only sales prices (as a opposed lender valuations) ensures that we are starting from an unbiased property value based on a market transaction. The second transaction can be either a sale (if the owners sell and move out) or a mortgage refinancing (if the owners do not sell). As explained in section 2 we can take the refinancing decision as quasi-exogenous as borrowers face higher interest rates if they do not refinance at the end of the introductory rate period.

We are interested in two types of effects. First, the treatment effects of *Flood (long)*, *Flood (short)* and *Risk Up* on sales prices. These are estimated using the change in value when the second transaction (post-flood) is a sale. The second effect is the valuation differential when the second transaction is a mortgage refinancing, instead of a property refinancing.

To estimate these effects we need to control for property and borrower-specific characteristics and local house price trends that can affect house prices and valuations. This repeat transaction (sale-sale, or sale-refinancing) approach controls for time-unvarying property and borrower-specific characteristics. Propensity score matching (described in section 3.2) already addresses comparability between treatment and control groups, but we also use available information on property and borrower characteristics to capture their effect on house appreciation. Local house price trends are controlled via interacted postcode district-year fixed effects. The district-year fixed effects also capture the effect on property values of variation in flooding experience *across* districts during the WF1314, and different appreciation caused by the time lapsed between the original property transaction and the subsequent refinancing or resale transaction. As a further control for selection bias, we add property and borrower characteristics.

We run the following specification:

$$
\begin{aligned}
\Delta Y_{i,c,k} =& ln\ Y_{i,c,k,post} - ln\ Y_{i,c,k,pre} = \\
& \beta_1 FL_c + \beta_2 FS_c + \beta_3 R_c + \beta_4 V_i + \\
& \beta_{14} V_i \times FL_c + \beta_{24} V_i \times FS_c + \beta_{34} V_i \times R_c + \\
& \gamma_k \times \lambda_1 + \gamma_k \times \lambda_2 + \theta X_i + \epsilon_{i,c,k} \qquad (1)
\end{aligned}
$$

where the outcome variable $\Delta Y_{i,c,k}$ is calculated as the difference between $ln\ Y_{i,c,k,post}$, the natural logarithm of the value of property i in postcode unit c and postcode district k in the post-flood period (which can be based on the price for an actual house sale or a valuation used for mortgage refinancing), and the natural logarithm of the value of the same property in the pre-flood period $ln\ Y_{i,c,k,pre}$ (always based on the price of a house sale).

FL_c, FS_c and R_c are flood (risk) treatment group dummies for postcode units that have experience long floods, short floods, and increases in risk (respectively). Their coefficients capture the treatment effect on prices for housing transactions.

The dummy V_i captures whether the second transaction (post-flood) for property i is a mortgage refinancing, and as a result the value variable $Y_{i,c,k,post}$ is based on the lender's valuation, rather than a sale price. The coefficient β_4 captures the average difference in appreciation for valuations for mortgage refinancing relative to sales prices. We interact V_i with the flood (risk) treatment dummies. The coefficients β_{14}, β_{24} and β_{34} reflect the differential effect of flood (risk) on valuation for mortgage refinancing, relative to prices for house sales.

γ_k are postcode dummies that restrict the analysis to a narrow local area, while λ_1 and λ_2 are dummies for the year of the first and second transactions (pre- and post-flood, respectively). We interact district and year dummies to remove the effects of local factors that cause house price trends to diverge across postcode districts. X_i reflects property and borrower characteristics (distance to water and property price and borrower loan-to-value for the first transaction).

In Table 2 we examine whether there is sufficient within-postcode district variation in flooding to estimate results after we include postcode district fixed effects. Panel A shows that 112 postcode districts experienced both flooding and an increase in flood risk, 321 an increase in flood risk only, and 40 flooding only. The remaining 159 districts experienced neither flooding nor an increase in flood risk, and there is no variation left to estimate within district effects (they only include observations in the control group, but none in the treatment groups). Panel B presents summary statistics for the share of properties in the 632 postcode districts in our sample that experienced flooding or an increase in flood risk. There is no postcode district where all properties are flooded or all properties experience an increase in flood risk. The maximum share of flooded properties in a postcode district is 66.7%, and the maximum share of properties for which flood risk increases is 72%. The average shares of properties affected by floods and flood risk are lower (1.4% and 4.1%, respectively), because several postcode districts were unaffected.

4 Results

In this section we first report results for the effect of the WF1314 on sales prices versus valuations. We then use a similar approach to check the effect on mortgage contract terms, and conclude discussing additional evidence supporting an interpretation of our results in terms of a "bias" in lender valuations.

4.1 Valuation differential

Table 3 presents results from running the specification in equation 1. We show results using both the full (unmatched) sample and two matched samples, first for flooding (where we match observations in the control group to those in *Flood (long)* and *Flood (short)*) then for increases in flood risk (where control observations are matched to those in *Risk up*). Our main results use the publicly available flood risk measure from the EA.

Column (1) in Table 3 shows results for the full sample and with interacted postcode district-year fixed effects. We see heterogeneity in the effect on house prices for $Flood$ ($long$), $Flood$ ($short$) and $Risk\ up$. $Flood$ ($long$) leads to a relative decrease in sales prices by 4.2%, while $Flood$ ($short$) has no significant effect on sales prices. Surprisingly, $Risk\ up$ leads to a small but significant increase (1.1%) in sales prices.

The coefficients on the interaction between treatment group dummies and valuation dummies capture the difference between valuations and sales prices. The differential effect of flood on valuations for mortgage refinancing, relative to prices for house sales, is 3.2% in the case of long floods ($Flood$ ($long$) $\times Valuation$), and statistically insignificant in the case of both short floods ($Flood$ ($short$) $\times Valuation$) and increases in risk ($Risk\ up \times Valuation$). Valuations for mortgage refinancing are on average 3.4% lower than comparable sales prices, possibly indicating a margin of conservatism applied by lenders.

These results have to be interpreted against a backdrop of rapid house appreciation. On average house values (considering both sales and refinancing transactions) increased by 21.8% in our sample.

In column (2) we replicate results using the matched sample on flooded properties. The results are similar although the magnitude of the effects of prolonged flooding on sales prices, and the related valuation differential is smaller: -3.3% and 2.9% for coefficients on $Flood$ ($long$) and $Flood$ ($long$) $\times Valuation$, respectively and the effects remain statistically significant, even if standard errors increase due to the smaller size of the matched sample. In column (3) we also add property-specific controls. The magnitude of the effect of prolonged flooding on sales prices declines further (-2.6%) but remains significant. The related valuation differential remains unchanged, and remains statistically significant.

In column (4) we use the matched sample on properties that experienced an increase in flood risk. The coefficient on $Risk\ up$ remains positive and significant (1%), and the valuation differential becomes significant (-1.2%). In column (5) we add property controls and both the magnitude and the statistical significance of the coefficients remain similar.

In unreported robustness checks, we remove outliers in two alternative ways, by winsorizing and by removing local authorities with very few observations. Results are qualitatively similar, but coefficients are lower when we winsorize.

In Table 4 we evaluate the importance of spill-over effects by relaxing the geographic fixed effects. Even non-flooded properties could be affected by flooding through damage to common public goods such as transport networks. If spillover effects are important, controlling for local house price trends with narrow geographic fixed effects will underestimate the treatment effect. One simple way to test for the importance of spillover effects is to relax the geographic fixed effects to include a wider area, which will include more properties that are located far away from the flood, and are hence less likely to experience spillover effects. We expect that if spillover effects are important, the coefficients on *Flood* (*long*) and *Flood* (*short*) will be higher than in our main specification in Table 3. In Table 4 we use local authority fixed effects (interacted with year fixed effects) instead of postcode district fixed effects. The coefficients are similar to those estimated using postcode district fixed effects, suggesting that spillover effects during the WF1314 were limited. The WF1314 were damaging, but not catastrophic, events and on a much smaller scale compared to, for example, US hurricanes. Permanent damage to public infrastructure may have been limited and house buyers may be unaffected by temporary disruptions.

4.2 Mortgage contract terms

In Table 5 we test the effect of flooding on two key mortgage characteristics, interest rate and loan amount. Column (1) shows results for interest rates using the full sample, including interacted district-year fixed effects, but not property controls. Interest rates increase by 31bp and 21bp in *Flood* (*long*) and *Flood* (*short*), respectively, and we do not observe a statistically significant effect of *Risk up*. In columns (2) and (3) we use the matched samples and add property controls. The coefficients on *Flood* (*long*) and *Flood* (*short*) decline to 14bp and 9bp respectively, and are no longer significant. The effect of *Risk up* on interest rate remains small and statistically insignificant.

In column (4) we show results for loan amounts for the full sample. Loan amounts increase for both *Flood* (*long*) and *Flood* (*short*), by 1.6% and 5.9% respectively, but the coefficient is (marginally) significant only for *Flood* (*short*). When we use the matched sample and add property controls, in column (5), the effect of *Flood* (*short*) on loan amount declines to 3.9% and is no longer statistically significant. The effect of *Flood* (*long*) becomes negative (-2.4%) and remains statistically insignificant. The coefficients for *Risk up* on loan amounts are small and statistically insignificant in both specifications in columns (4) and (6).

The results for the full sample indicate that lenders may charge a higher interest rate to refinance loans for properties that suffered prolonged flooding. But the results for the full sample are not robust to matching and adding property controls, suggesting that they may be explained by differential trends between low- and high-risk mortgages (e.g. because borrowers in the flood treatment groups have lower loan-to-value ratios). In short, we do not find evidence that lenders adjust substantially their mortgage contract terms in response to flood (risk).

4.3 Discussion

To complete the discussion of the results, we provide supporting evidence for an interpretation of the differential between sales prices and valuations as a "bias" in lender valuations. First, we show that lenders update valuations using house price indexes at a level of aggregation that does not (fully) capture the local effects of flooding. Second, we present evidence that the WF1314 provided new information on flood risk, in particular in areas where flooding was particularly long. Third, we support our interpretation in terms of risk information by showing that differences in home quality, proxied by loans for home improvements, are unlikely to explain our results.

4.3.1 House price indexes

Banks can update valuations in different ways. They can send surveyors to inspect the property or perform desk-based valuations. The latter in turn can be based on automated valuation models (AVMs) or track house price indexes. Desk-based valuations are cheaper than surveyors, and the implementation of AVMs for mortgage lending is still at a relatively early stage. Valuations in our sample appear to be based on published house price indexes that aggregate transaction data at local authority or regional level.[11]

We show that the correlation between sales prices and valuations in our sample increases as we aggregate data for wider geographic units. First, we merge sales prices and valuations at *postcode unit*. For each postcode unit, which consists of 16 properties on average, we compute the average change in sale price and the change in valuation for refinancing purposes. This ensures that we are comparing sales and refinancing transactions for properties in a very narrow area, with similar exposure to flooding. As before, we use only repeat transactions to control for property characteristics.

In Figure 3, scatterplot (a) each observation is a postcode unit. The average change in sale prices is shown on the horizontal axis, and the average change in valuation is shown on the vertical axis. If lenders update valuations using sales prices in the same postcode unit, the slope of scatterplot should be close to one—valuations should change in line with local prices. Instead, the slope of the scatterplot is much flatter (the correlation coefficient is 0.26).

Scatterplot (b) compares average changes in sales prices at the level of *local authorities*. The slope is much closer to one than at the postcode unit level (the correlation coefficient is 0.95). Finally, scatterplot (c) shows observations at the *regional* level, and the slope is one, indicating that at this level of aggregation changes in valuations perfectly track changes in house prices.

4.3.2 Flood risk information

Next, we investigate the likely drivers of local flood-related house price variation. Flooding can affect house prices through different channels. It can provide new information to

[11]The most common indexes in the UK are published by the Office of National Statistics, and by Nationwide and Halifax, two large mortgage lenders.

update flood risk models (which are also reflected in insurance premiums), and also change households' perceptions about the risk. The quality of a property after a flood can be below or above the original standard, depending on whether repairs compensate for the damage done by the flood, or even increase the standard of a property (e.g. by replacing old fixtures with new ones). In this case, the coefficients on $Flood$ ($long$) and $Flood$ ($short$) capture the extent to which these characteristics change at a different rate for properties that flooded versus the control group of non-flooded properties. We do not attempt to fully disentangle these channels, as our main focus is on the differential between valuations and sales prices. We provide however descriptive evidence on changes in quality and risk measures in flooded versus non-flooded areas.

We can use changes in our measures of flood risk *after* the flood to test whether the WF1314 provided new information.[12] If the floods were already fully anticipated by flood risk models, updates following the WF1314 should not result in higher flood risk. An increase in risk post-flood risk, on the contrary, would provide evidence that the WF1314 yielded new information to update models. Table 6 shows post WF1314 changes in EA and JBA risk measures by group. (As described in Section 2, EA risk measures are publicly available and used by surveyors and solicitors during house sale transactions. JBA provides risk services to the insurance industry, and its measures are used to set underwriting standards and pricing.) For both EA and JBA measures we observe a larger ex-post increase in flood risk in areas hit by WF1314 (and more so for long than for short floods), but not in the control group of non-flooded areas. The difference is statistically significant for the JBA Matrix Score, but not for the EA measure. This result suggests that 1) the decline in house prices in (long) flooded areas could be attributed to new information about flood risk, and 2) insurance premiums may be a more important channel than public information to embed information of flood risk in house prices.

[12]The *Risk up* control group is constructed using changes in EA flood risk models that were released roughly with (but measured before) the WF1314.

For both the EA and JBA measures, the magnitude of the ex-post change in flood risk for *Flood* (*long*) is about double the change for *Flood* (*short*), which is consistent with the (significant) negative house price effect in *Flood* (*long*), but not *Flood* (*short*) in Table 3.

4.3.3 Housing quality

Since we cannot observe the effect of flooding on the quality of individual properties (this would require additional information, such as insurance claims), we cannot exclude that our results are affected by changes in property characteristics. A first concern is that the intensity of flooding varies between properties that are refinanced versus properties that are sold, for example as a result of self-selection (the worst hit households may prefer to sell). In our specification we control for the intensity of flooding both by varying treatment with flood length (longer floods are likely to make more lasting damage), and by comparing properties within the same postcode district (which removes some of the geographic variation in flooding characteristics). We observe flood intensity and flood risk measures at the postcode unit level. Flood risk variation within postcode units is limited (with the caveat of apartment blocks where there is minimal flood risk above ground level). Measurement error for flood duration (our measure of intensity) increases with granularity.

We can use information available on mortgages for loan improvement to proxy for home improvement activity. The Product Sales Data includes information on the purpose of mortgage loans, including home improvement. This information is only reported for a minority of loans, but we can use it to check for differential trends in home improvement between flooded and non-flooded areas. Table 7 compares refinancing activity for home improvement in the post-WF1314 period across treatment and control groups. We do not observe any significant difference, suggesting that properties in flooded areas were not substantially under- or over-renovated compared to those in non-flooded areas, and that, as a result, their change in quality is likely to have been similar. We observe a small difference between *Flood* (*long*) and *Flood* (*short*) properties, but it is not statistically significant.

5 Conclusions

In this paper, we examine how lenders account for extreme weather by comparing matched repeat mortgage refinancing and property transactions around a severe flood event in England in 2013-14. Our results suggest that lender valuations do not "mark-to-market" against local price declines. And lenders do not offset this valuation bias by adjusting interest rates or loan amounts. Overall, this suggests that lenders do not track closely the impact of extreme weather *ex-post*. Instead, we provide evidence that lenders track house price indexes at a level of aggregation that is too high to capture local variation in house prices after flooding.

For lenders, over-valued refinancing valuations can result in under-pricing of credit risk, but can also help attract borrowers who shop around for the best mortgage terms. Our results focus on refinancing, and further research could assess how lenders take into account flood risk in new mortgage origination. For households, biased valuations can attenuate the financial consequences of extreme weather events. In our sample, however, the households most exposed to flooding tend to be lower risk, suggesting that they may able to withstand a deterioration in refinancing terms. By over-valuing housing collateral, lenders and households may become over-exposed to assets prone to flooding, and to sharp reassessments of climate-related risks. This might not only hold true for the specific risk (flooding) and asset (housing) studied in this paper, but also for other physical risks related to climate.

Using house price indexes to underwrite mortgages also creates an implicit cross-subsidy from low to high flood risk properties. Under-pricing of risks to some properties can be offset by over-pricing of risks for others, and the net effect on the riskiness of a lender's mortgage portfolio is not clear. Other shocks, beyond flooding, that affect the relative value of properties in a local area (e.g. new infrastructure) might have similar effects, but the cross-subsidy may disappear as lenders roll out automated valuation models that exploit granular local information.

Policymakers have recently started to consider the implications of climate change for the safety and soundness of financial institutions and for financial stability. Proposals include varying banks' capital requirements according to their exposure to physical and transition risks from climate change (European Commission, 2018; Boot and Schoenmaker, 2018), and enhanced climate-related financial disclosures (Task Force on Climate-related Financial Disclosures, 2018). Regulators are also starting to assess lenders' business models against future extreme weather shocks, for example by developing stress test scenarios that take into account climate change (Network for Greening the Financial System, 2018; Bank of England, 2018, 2019). Our exercise speaks to this debate, and indicates that a) valuations are an important channel to price, and regulate, climate-related risks for less liquid assets such as real estate; and b) the geographic granularity of the scenarios can affect stress testing results.

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Table 1: Summary statistics

Panel A. Property characteristics

	Flood (long)	Flood (short)	Risk up	Control		
				Full	Matched Flood	Matched Risk up
	(1)	(2)	(3)	(4)	(5)	(6)
Property value	402,382	269,422	226,088	237,648	389,701	206,140
Distance to water	229	270	478	745	302	447
Risk (EA) (2013)	1.30	0.64	0.88	0.07	0.49	0.36
Matrix Scores (JBA) (2013)	17.74	10.89	11.28	2.93	10.21	8.82
Observations	731	679	4,615	113,214	7,619	18,948

This table shows mean values of property characteristics, Property value, Distance to water (in m), Risk (EA) (2013) (in %), Matrix Scores (JBA) (2013) by treatment groups, Flood and Risk up, and control groups (full sample, matched (flood), matched (risk up).

Panel B. Borrower characteristics (69% of all transactions)

	Flood (long)	Flood (short)	Risk up	Control		
				Full	Matched Flood	Matched Risk up
	(1)	(2)	(3)	(4)	(5)	(6)
LTV	69.72	69.01	72.52	73.09	70.34	73.85
LTI	3.40	3.26	3.31	3.32	3.25	3.24
Loan amount	264,899	180,193	167,600	167,427	212,849	154,843
Gross income	97,558	77,136	66,539	63,979	95,302	60,397
Age	38.11	38.01	36.55	35.53	36.87	35.33
Observations	508	406	2,988	78,389	5,277	12,484

This table shows mean values of mortgage borrower characteristics, LTV, LTI, Loan amount, Gross income, Age by treatment groups, Flood (long), Flood (short), Risk up, and control groups (full sample, matched (flood), matched (risk up).

Panel C. Change in property prices (sales)

	Flood (long)	Flood (short)	Risk up	Control		
				Full	Matched Flood	Matched Risk up
	(1)	(2)	(3)	(4)	(5)	(6)
D.Property value (Ln)	0.27	0.19	0.23	0.23	0.22	0.22
Observations	448	474	3,221	76,349	5,000	13,271

This table shows mean values of the change in the natural logarithm of the sales price by treatment groups, Flood (long), Flood (short), Risk up, and control groups (full sample, matched (flood), matched (risk up).

Panel D. Change in property valuations (mortgage refinancing)

	Flood (long)	Flood (short)	Risk up	Control		
				Full	Matched Flood	Matched Risk up
	(1)	(2)	(3)	(4)	(5)	(6)
D.Property value (Ln)	0.25	0.16	0.19	0.19	0.19	0.19
Observations	283	205	1,394	36,865	2,619	5,677

This table shows mean values of the change in the natural logarithm of the property valuation by treatment groups, Flood (long), Flood (short), Risk up, and control groups (full sample, matched (flood), matched (risk up).

Table 2: Districts affected by floods and risk increases

Panel A. Number of postcode districts by flooded and risk up

	At least one risk up		
At least one flooded	No	Yes	Total
No	159	321	480
Yes	40	112	152
Total	199	433	632

Panel A of this table shows the number of postcode districts affected by floods and risk increases.

Panel B. Share of treated postcode units per postcode district

	Obs	Mean	Std. Dev.	Min	Max
Flooded	632	0.014	0.047	0.000	0.667
Risk up	632	0.041	0.071	0.000	0.721

Panel B shows the share of postcode units affected by floods and risk increases per postcode district.

Table 3: Change in property values

Dependent variable	D.Property value (Ln)				
Sample	Full	Matched		Matched	
Column	(1)	(2)	(3)	(4)	(5)
Flood (long)	-0.042***	-0.033***	-0.026**		
	(0.009)	(0.012)	(0.012)		
Flood (short)	-0.004	0.018	0.021		
	(0.012)	(0.020)	(0.019)		
Risk up	0.011**			0.010**	0.018***
	(0.004)			(0.005)	(0.005)
Flood (long) x Valuation	0.032***	0.029**	0.029*		
	(0.010)	(0.014)	(0.015)		
Flood (short) x Valuation	0.008	0.004	0.007		
	(0.021)	(0.029)	(0.029)		
Risk up x Valuation	-0.006			-0.012**	-0.013**
	(0.005)			(0.006)	(0.006)
Valuation	-0.034***	-0.035***	-0.012	-0.029***	-0.003
	(0.001)	(0.008)	(0.008)	(0.003)	(0.003)
District x Year FE	YES	YES	YES	YES	YES
Property controls	NO	NO	YES	NO	YES
Observations	119,492	8,129	8,129	22,994	22,994
Long flood	728	713	713	0	0
Short flood	683	597	597	0	0
Risk increase	4,635	0	0	4516	4516
R2	0.218	0.316	0.353	0.298	0.34
Mean of dep. variable	0.216	0.217	0.217	0.212	0.212

This table shows regression results where the dependent variable is the change in the natural logarithm of the property value (sales price for sales transactions and property valuation for mortgage transactions). Main explanatory variables are Flood (long), Flood (short) and Risk up as well as their interactions with Valuation. The sample consists of properties sold both at least once in the three year window before the flood event as well as either resold or refinanced in the three year window after the flood event. All columns control for District x Year FE of both the first and the second transaction. Column (1) shows the result using the full sample. Columns (2)-(5) show results using the matched sample. Columns (3) and (5) include property controls (propery value and LTV in the first transaction as well as the distance to water). Time window is [-3; 3] years relative to the 2013/14 flood. Standard errors clustered at the postcode district and reported in brackets. Stars denote statistical significance at the 0.01 & 0.05 & 0.10-level respectively.

Table 4: Change in property values (Local Authority x Year FE)

Dependent variable	D.Property value (Ln)				
Sample	Full	Matched		Matched	
Column	(1)	(2)	(3)	(4)	(5)
Flood (long)	-0.038***	-0.030***	-0.028***		
	(0.008)	(0.010)	(0.011)		
Flood (short)	-0.005	0.007	0.006		
	(0.012)	(0.016)	(0.016)		
Risk up	0.011**			0.007	0.015***
	(0.004)			(0.005)	(0.005)
Flood (long) x Valuation	0.035***	0.034***	0.030**		
	(0.010)	(0.012)	(0.014)		
Flood (short) x Valuation	0.007	0.010	0.015		
	(0.020)	(0.025)	(0.025)		
Risk up x Valuation	-0.006			-0.007	-0.008
	(0.005)			(0.006)	(0.006)
Valuation	-0.033***	-0.037***	-0.013*	-0.030***	-0.005
	(0.001)	(0.006)	(0.007)	(0.003)	(0.003)
Local Authority x Year FE	YES	YES	YES	YES	YES
Property controls	NO	NO	YES	NO	YES
Observations	119,208	8,923	8,923	23,505	23,505
Long flood	731	722	722	0	0
Short flood	679	648	648	0	0
Risk increase	4,612	0	0	4,587	4,587
R2	0.182	0.184	0.215	0.191	0.23
Mean of dep. variable	0.216	0.215	0.215	0.212	0.212

This table shows regression results where the dependent variable is the change in the natural logarithm of the property value (sales price for sales transactions and property valuation for mortgage transactions). Main explanatory variables are Flood (long), Flood (short) and Risk up as well as their interactions with Valuation. The sample consists of properties sold both at least once in the three year window before the flood event as well as either resold or refinanced in the three year window after the flood event. All columns control for Local Authority x Year FE of both the first and the second transaction. Column (1) shows the result using the full sample. Columns (2)-(5) show results using the matched sample. Columns (3) and (5) include property controls (propery value and LTV in the first transaction as well as the distance to water). Time window is [-3; 3] years relative to the 2013/14 flood. Standard errors clustered at the postcode district and reported in brackets. Stars denote statistical significance at the 0.01 & 0.05 & 0.10-level respectively.

Table 5: Change in mortgage contract terms

Dependent variable	D.Mortgage rate			D.Loan amount (Ln)		
Sample	Full	Matched		Full	Matched	
Column	(1)	(2)	(3)	(4)	(5)	(6)
Flood (long)	0.307***	0.140		0.016	-0.024	
	(0.093)	(0.114)		(0.024)	(0.025)	
Flood (short)	0.205*	0.088		0.059*	0.039	
	(0.116)	(0.159)		(0.031)	(0.049)	
Risk up	-0.035		0.004	-0.003		0.002
	(0.045)		(0.061)	(0.014)		(0.015)
District x Year FE	YES	YES	YES	YES	YES	YES
Property controls	NO	YES	YES	NO	YES	YES
Observations	25,466	1,299	3,763	38,341	2,191	6,229
Long flood	196	180	0	281	265	0
Short flood	130	72	0	200	127	0
Risk increase	881	0	734	1,370	0	1,252
R2	0.176	0.522	0.475	0.105	0.444	0.367
Mean of dep. variable	-1.485	-1.364	-1.511	0.019	0.017	0.014

This table shows regression results where the dependent variable is the change in the mortgage rate (columns (1)-(3)) and the change in the natural logarithm of the loan amount (columns (4)-(6)). Main explanatory variables are Flood (long), Flood (short) and Risk up as well as their interactions with Valuation. The sample consists of properties sold both at least once in the three year window before the flood event as well as either resold or refinanced in the three year window after the flood event. All columns control for District x Year FE of both the first and the second transaction. Columns (1) and (2) show the result using the full sample. Columns (2)-(3) and (5)-(6) show results using the matched sample. Columns (3) and (5) include property controls (propery value and LTV in the first transaction as well as the distance to water). Time window is [-3; 3] years relative to the 2013/14 flood. Standard errors clustered at the postcode district and reported in brackets. Stars denote statistical significance at the 0.01 & 0.05 & 0.10-level respectively.

Table 6: Ex-post changes in risk and ex-ante risk

	Flood long (1)	Flood short (2)	Risk up (3)	Control (4)	Difference (1)-(4) (5)	Difference (2)-(4) (6)	Difference (3)-(4) (7)
D. Risk (2016-2014) (EA)	0.03	0.02	-0.11	0.01	0.02	0.01	-0.12***
D. Risk (2017-2013) (JBA)	3.19	1.30	1.64	0.58	2.61***	0.72*	1.05***
Risk (2013) (EA)	1.35	0.66	0.86	0.07	1.28***	0.59***	0.79***
Risk (2013) (JBA)	17.60	10.40	11.04	2.87	14.73***	7.53***	8.17***
Number of postcode units	502	482	3,182	75,152	75,654	75,634	78,334

Columns (1)-(4) of this table show the change in risk between 2016 and 2014 as measured by the Environment Agency, D. Risk (2016-2014) (EA), the change in risk between 2017 and 2013 as measured by JBA Matrix Scores, the level of flood risk in 2013, as measured both by the Environment Agency and JBA, by treatment groups, Flood long, Flood short and Risk up, and the control group. Observations are collapsed to the postcode unit level which is the unit of observation. Columns (5)-(7) show mean differences. Stars denote statistical significance at the 0.01 & 0.05 & 0.10-level respectively.

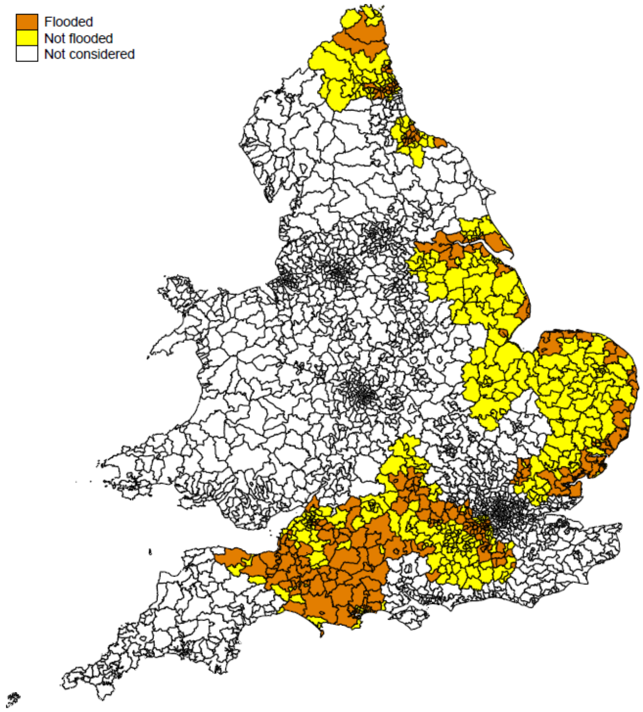
Table 7: Home improvement

	Flood long (1)	Flood short (2)	Risk up (3)	Control (4)	Difference (1)-(4) (5)	Difference (2)-(4) (6)	Difference (3)-(4) (7)
Mortgages for home improvement	0.10	0.12	0.11	0.11	-0.01	0.01	0.01
Number of mortgages	564	409	2,759	73,222	73,786	73,631	75,981

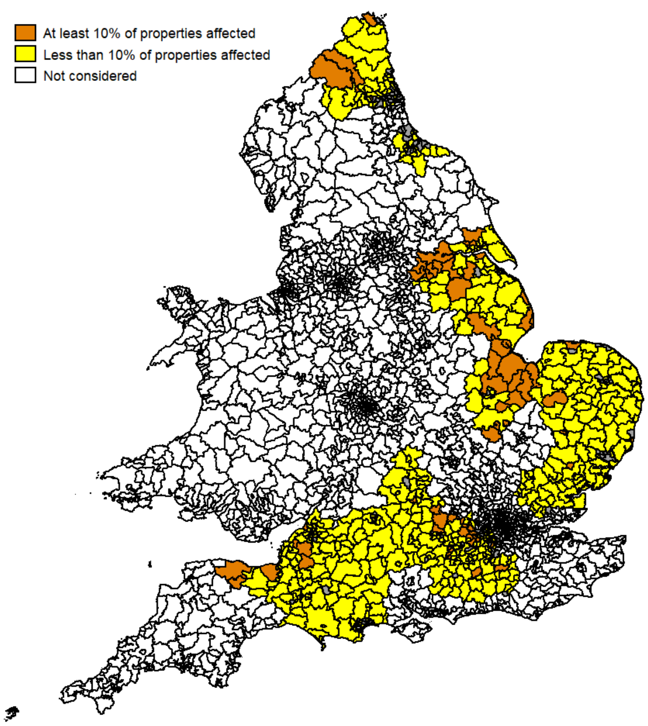
Columns (1)-(4) of this table shows the share of mortgages used for home improvement by treatment groups, Flood long, Flood short and Risk up, and the control group in the second event window after the flood. The observations are on the mortgage level. Columns (5)-(7) show mean differences. Stars denote statistical significance at the 0.01 & 0.05 & 0.10-level respectively.

Figure 1: Flood maps

(a) Flood



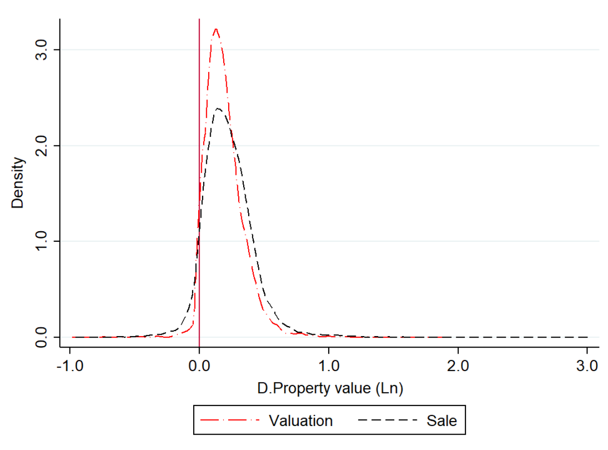
(b) Risk increase



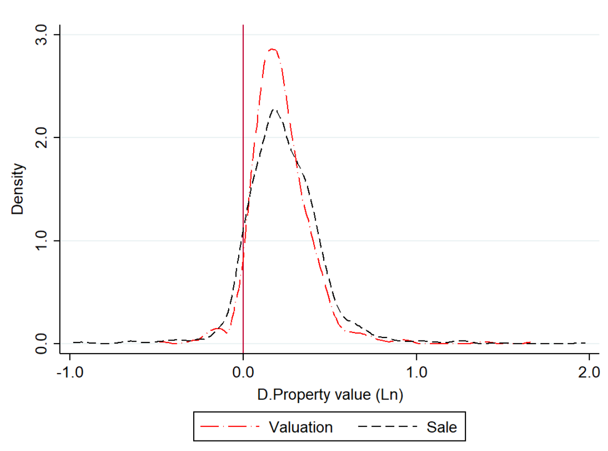
These maps show the postcode districts affected by the 2013/14 Winter Flood and by increases in flood risk.

Figure 2: Distribution of the change in property values

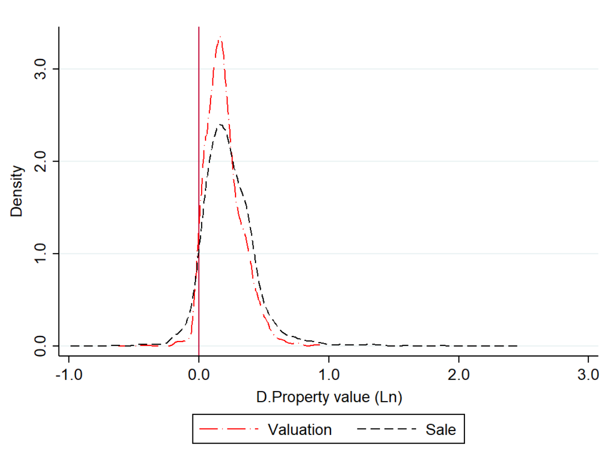
(a) Control



(b) Flood



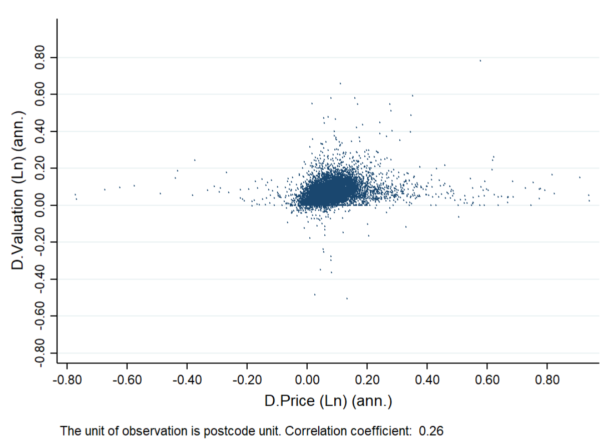
(c) Risk increase



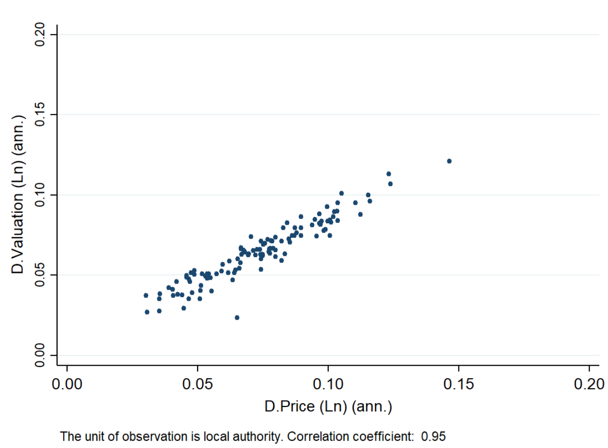
These graphs show the distribution of the change in property values (sales prices and property valuations for refinancing mortgages) by treatment groups (flood, risk increase) and control group.

Figure 3: Change in property valuations vs. sales price

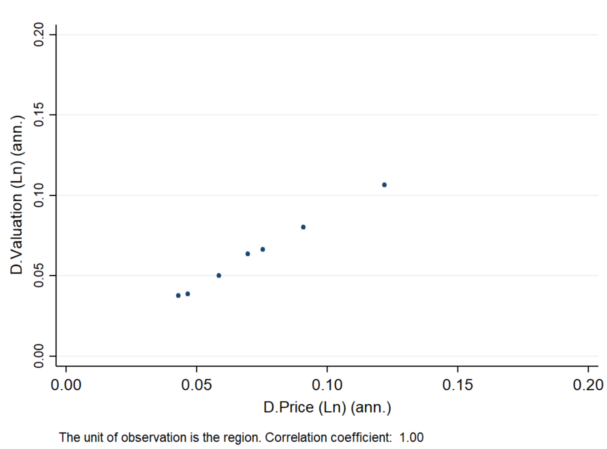
(a) Postcode unit



(b) Local Authority



(c) Region



These graphs show scatterplots of the change in property valuation vs sales price at different levels of aggregation (postcode unit, local authority, region). We exclude local authorities with less than 80 observations.