Map Updates and Flood Events on Kentucky's Housing Market*

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Abstract

Assessing the flood risk belief associated with flood maps and flooding events is crucial for land-use regulations and flood preparation plans, particularly with the increasing prominence of extreme weather in recent years. Using Zillow's ZTRAX property transaction data and FEMA's floodplain maps, this paper looks at the effects of map changes and flooding events on Kentucky's housing market. I show that housing values decrease by 6.5% when a property is mapped into a floodplain in an area that has experienced a large flood within a year and increase by 4% when a property is removed from a floodplain in an area without one recently. The findings provide evidence that individuals' responses to changes in flood risk are based on both recent flooding events and FEMA flood maps and that the changes in flood zone status alone might not be a strong signal for increased risks.

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1 Introduction

Flood events are the most common and costly natural disasters in the U.S., affecting millions of individuals each year. According to the National Centers for Environmental Information, the U.S. has witnessed over $67.8 billion in flood damages since 2010 (Smith, 2020). In Kentucky, flooding is the state's most frequent and costly natural disaster[1]. Kentucky's varying degrees of topography play a role in the state's vulnerability to flooding. Figure 1 shows the ratio of total property damage by floods to median home value in the last 2 decades. At the end of July 2022, several counties in Eastern Kentucky were hit by severe flash floods resulting from a week-long heavy rain. The "1-in-1000 year"[2] flood event claimed more than 30 lives and destroyed hundreds of homes, bridges, and roads in the area. Unfortunately, most residents in this area have not had flood insurance because they are not in a floodplain and 6 of those counties do not have an updated flood maps since 2009.

While climate events and their impact on real estate assets are not unprecedented, the increasing prominence of extreme weather in the past few decades has become more apparent. Climate change, population growth, and changes in land use have exposed more people to flood hazards. Flood damages are expected to increase annually, where the financial consequences are being borne by homeowners and the government (FEMA, 2022). This creates difficulties for the Federal Emergency Management Agency (FEMA) to accurately quantify a property's risk as flood risks change over time, and thus presents a challenge to all those engaged in the housing market, whether as potential homeowners making housing decisions, as insurers setting actuarially fair insurance rates, or as policymakers choosing appropriate land-use regulations and flood preparation plans.

Economists have been examining the impact of negative shocks from natural disasters on risk attitudes and perceptions. Individuals may process risks according to a Bayesian learning process, which suggests that individuals update their prior risk beliefs in response to new information. In the case of flooding, there is publicly available information on the likelihood of an event (flood risk maps) and historical flood records for people to adjust their risk beliefs. For example, individuals

[1] Estimates are based on the Storm Events Database from NOAA/National Centers for Environmental Information (NCEI). Digital data are available at http://www.ncdc.noaa.gov/stormevents/ftp.jsp

[2] According to the United States Geological Survey (USGS), the term "1,000-year flood" means that a flood of that magnitude (or greater) has a 1 in 1,000 chance of occurring in any given year. In terms of probability, the 1,000-year flood has a 0.1% chance of happening in any given year.

who recently experienced a flood event will likely increase their perception of risk and exhibit higher levels of risk aversion afterward (Tversky and Kahneman, 1973). I focus on the housing market's responses to flood risk as a means to adapt to climate change. The housing literature relevant to flood risk suggests that the correction of flood risk will affect home values because home buyers will account for changes in insurance (if changes in flood risks are reflected in insurance payments) and expected damages.

In 1968, Congress passed the National Flood Insurance Act, tasking the Federal Emergency Management Administration (FEMA) with creating and facilitating the NFIP. The NFIP's stated purpose is twofold: 1) to provide access to federally subsidized flood insurance and distribute the cost of flooding and 2) to reduce the nation's flood risk through the implementation of floodplain management standards. To accomplish these goals, the NFIP requires communities to work collaboratively to employ flood risk mitigation strategies and develop Flood Insurance Risk Maps (FIRM). FIRMs delineate Special Flood Hazard Areas (SFHA), which are areas that have a 1% or greater risk of flooding every year. In communities that participate in the NFIP, homeowners of properties in the SFHA are required to purchase flood insurance as a condition of receiving federally backed mortgages or federally regulated mortgages. Moderate to low-risk areas are marked as 500-year floodplains, where the properties have 0.2% flooding risk every year but are not required to purchase flood insurance. The old flood insurance premium rating, which had not fundamentally changed since the 1970s, evaluated the properties by the structures' flood risk zone on floodzone status, the elevation of the structure relative to the Base Flood Elevation (BFE) in each risk zone, and the occupancy type. Taking effect on all NFIP policyholders in April, 2022, a new premium rating system, Risk Rating 2.0, calculates flood insurance premiums by incorporating a broader range of measures such as the distance to water, the type and size of nearest bodies of water, flood frequency and the elevation of the property relative to the flooding source. According to FEMA, Risk Rating 2.0 will reflect more types of flood risk in the premium rates and provide rates that are easier for policyholders to understand.

Given that the severity of flooding is expected to increase over time, the National Flood Insurance Program Reform Act of 1994 mandated FEMA to review the FIRMs every five years. However, there is no consistent timetable for when a particular community will have its maps revised and updated. Generally, flood maps may require updating when there have been significant new building developments in or near the flood zone, changes to flood protection systems, or environmental changes in the community. Because of the variability in how and when a FIRM is updated, one community may have had its map last updated in 2018 while a neighboring community had its last revised in 2005. Figure 2 shows the years in which each county had its last map updates. Of 120 counties in Kentucky, 63 counties have not updated their flood maps since 2011.

This paper uses flood map updates and flood events in Kentucky to investigate how the housing market responds to flood risks associated with different information: observed flooding and the flood hazard maps put forth by FEMA. This study asks two questions: How does the housing market respond to a change in floodplain status? Second, does the housing market response differ depending on how the update in flood risk information occurs (e.g., due to flood-related events as opposed to an update in flood maps)? I use Zillow's ZTRAX property transaction data and current and historical floodplain maps to conduct a hedonic property price model and estimate the price difference of the residential properties with a change in the flood zone status. I find that the properties that are switched into the floodplain in an area that has experienced a large flood within a year saw a decrease in price and the property price increases when a house is removed from a floodplain in an area without flooding within a year. In heterogeneity analysis, I also find that the housing markets' responses to flood risk vary by neighborhood characteristics. These findings are consistent under several checks for robustness, including limiting the sample to sales within 500m of flood map boundaries.

The study contributes to the hedonic literature that examines the impacts of flooding on the housing market. Previous studies show that locating within a flood zone lowers the property value more after a major flood event (Bin and Polasky, 2004; Kousky, 2010; Bin and Landry, 2013). However, the immediate post-flood discount for properties inside the floodplain diminishes with time (Atreya et al., 2013; Beltrán et al., 2019). Literature also shows that there is negative risk salience effect for high-risk properties that are not actually inundated (Bakkensen et al., 2019; Hennighausen and Suter, 2020; Yi and Choi, 2020). To my knowledge, this paper provides the first evidence of the effects of the impact of multiple large regional floods on the housing market within one inland state over time.

Additionally, the paper contributes to the recent literature that uses changes in flood risk mapping to identify preferences to avoid flood risk. Empirical work has shown that the sale prices of previously flood-free properties being assigned into flood zones decrease (Hino and Burke, 2020) but properties previously located in flood zones that become flood-free see no significant impact on sale prices (Shr and Zipp, 2019). Gibson and Mullins (2020) show that after Hurricane Sandy, properties in New York City included in the new floodplain experienced a large price discount compared to those who are not in the new floodplain. Furthermore, home buyers are more responsive to the actual occurrence of a flood event than to the release of flood maps to the public (Rajapaksa et al., 2016). My paper will extend this literature by studying the effects of both changes in the flood maps and flood events on the housing market showing how different sources of flood risk information may have varying, interactive effects on the housing market.

The paper proceeds as follows. The first section introduces the background and related literature. The second section shows details on the data and variables of interest. The third section presents the research design and identification strategies. The fourth section presents the results. The fifth section assesses robustness. Finally, the sixth section concludes and discusses the limitations of the study.

2 Theory

I apply a Bayesian learning model (Viscusi, 1991) to formulate an individual's subjective perceptions of flood risk as a Bayesian learning process (Gayer et al., 2000). Individuals are assumed to update their prior probability assessment of flood risk based on both new information provided by FEMA and flood events. The updated subjective probability of flooding (π) is a function of the risk from the new information, which includes flood map updates (m) and flooding events (e), and the individual's prior risk belief (k) that is based on the previously assigned flood zone and past experience with flood events:

$$\pi(k,m,e) = \frac{\phi_0 k + \kappa_0 m + \psi_0 e}{\phi_0 + \kappa_0 + \psi_0} \tag{1}$$

where ϕ_0, κ_0 and ψ_0 are the information parameters which measure information content associated with, respectively, the prior risk assessment, flood map updates, and flooding events. Denote the weight of each information source on an individual's risk belief as $\phi = \frac{\phi_0}{\phi_0+\kappa_0+\psi_0}$, $\kappa = \frac{\kappa_0}{\phi_0+\kappa_0+\psi_0}$ and

$\psi = \frac{\psi_0}{\phi_0+\kappa_0+\psi_0}$. The risk-perception function can be re-written as

$$\pi(k, m, e) = \phi k + \kappa m + \psi e \tag{2}$$

The new information may serve as good news or as bad news, therefore, m and e may be less or greater than k. If a house is moved outside of the floodplain, $m < k$, then the individual would lower their risk beliefs. If a house is re-zoned to be in a floodplain, $m > k$, then the individual would increase their risk belief. If new flood maps do not provide any new information to the individuals, the risk belief would remain the same. If a flooding event caused damages to the house or the surrounding areas, we would expect that $e > k$ and the individual would increase their risk belief.

I extend the models of MacDonald et al. (1987); Hallstrom and Smith (2005); Bin and Landry (2013); Kousky (2010); Shr and Zipp (2019) by accounting for the information of flood map updates and recent flood events. The decision is modeled using a state-dependent expected utility framework, where there are two states: flooding (F) and no flooding (NF). Let U_F denote the utility in the flooding state and U_{NF} as the utility when there is no flood. Three assumptions are necessary to establish the household decision making problem: (1) For any given level of income, households prefer being safe, i.e. $U_{NF} > U_F$ (2) Within each state of the world, households are risk-neutral or risk-averse (utility function is quasi-concave); (3) Marginal utility of income is higher when there is no risk. Household utility in each state of the world is defined as:

$$U = U(X, Z) \tag{3}$$

where X is a numeraire good and the price is set equal to 1; Z is the set of neighborhood and structural characteristics of the home. The function $P()$ maps housing characteristics, neighborhood attributes, and individuals' risk perceptions to a price:

$$P = P(Z, \pi(k, m, e)) \tag{4}$$

Given total income Y, individuals choose the level of X and Z to maximize their utility subject to their budget constraint:

$$\begin{aligned} Max\ EU &= \pi(k,m,e)U(X_F,Z) + [1-\pi(k,m,e)]U(X_{NF},Z) \\ s.t.\ Y &= X + P(Z,\pi(k,m,e)) \end{aligned} \tag{5}$$

The numeraire X can be expressed as $X_{NF} = Y - P(Z,\pi(k,m,e)) - I(k,m)$ when no flood occurs and as $X_F = Y - P(Z,\pi(k,m,e)) - I(k,m) - L + C$ in the case of a flood. I is the flood insurance premium payment[3]; L is the loss during a flood event; and C is the insurance coverage for a flood event.

The expected utility can be rewritten as

$$\begin{aligned} EU = \pi(k,m,e)U(Y - P(Z,\pi(k,m,e)) - I(k,m) - L + C, Z) \\ + [1-\pi(k,m,e)]U(Y - P(Z,\pi(k,m,e)) - I(k,m), Z) \end{aligned} \tag{6}$$

Under the assumptions that the housing market is a perfectly competitive and the consumers are rational, have identical preferences, perfect information, and perfect mobility,[4] we can solve for the partial derivative of the hedonic function with respect to the risk belief, which gives the marginal implicit price of the risk, or the risk discount.

$$\frac{\partial P}{\partial \pi} = \frac{U_F - U_{NF}}{\pi \frac{\partial U_F}{\partial X} + (1-\pi)\frac{\partial U_{NF}}{\partial X}} < 0 \tag{7}$$

Using the chain rule, we can solve for the partial derivatives of the hedonic function with respect to each information source. The marginal implicit prices of the risk prior to a new event, the risk associated with the new flood zone information, the risk associated with a new flooding event are, respectively,

$$\frac{\partial P}{\partial k} = \frac{\partial \pi}{\partial k}\frac{\partial P}{\partial \pi} - \frac{\partial I}{\partial k}, \qquad \frac{\partial P}{\partial m} = \frac{\partial \pi}{\partial m}\frac{\partial P}{\partial \pi} - \frac{\partial I}{\partial m}, \qquad \frac{\partial P}{\partial e} = \frac{\partial \pi}{\partial e}\frac{\partial P}{\partial \pi} \tag{8}$$

The Bayesian model suggests that people will increase or decrease their willingness to pay for

[3]The NFIP rating methods during the sample period used basic characteristics to classify properties based on flood risks, which are evaluated by the flood zone, occupancy type and the elevation of the structure.

[4]Property prices are higher in an area with better amenities because households would want to move into the areas and drive up the prices. Perfect mobility of households between different locations ensures that the property prices reflect the benefits of amenities.

risk reduction after the release of the new map by FEMA or a flooding event. The impact of the new information enters the hedonic price analysis by a comparison of the marginal price of the risk before ($\frac{\partial P}{\partial k}$) and after ($\frac{\partial P}{\partial \pi}$) such events. I discuss the impact of new information on the implicit marginal price of flood risks in three cases.

Case 1: Properties mapped into floodplain

Mapping a property into a floodplain increases the individual's risk belief and requires the individual to purchase flood insurance ($\frac{\partial I}{\partial m} > 0$). The effect of the new information would have a negative impact on housing prices and we would expect an increase in willingness to pay for risk reduction ($\frac{\partial P}{\partial \pi} > \frac{\partial P}{\partial k}$).

Case 2: Properties mapped out of floodplain

For properties mapped outside of a floodplain, the change indicates that flood risk is lower than previously perceived. The individual's risk belief will decrease and they would no longer be required to purchase flood insurance ($\frac{\partial I}{\partial m} < 0$). The effect of the new floodplain status would have a positive impact on housing prices and we would expect a decrease in willingness to pay for risk reduction ($\frac{\partial P}{\partial \pi} < \frac{\partial P}{\partial k}$).

Case 3: Properties that experience a flooding event

Previous studies have confirmed that following a flood event, there is a significant negative effect on the value of properties at risk ($\frac{\partial P}{\partial e} < 0$). Individuals will increase their risk belief and the new information would cause an increase in willingness to pay for risk reduction ($\frac{\partial P}{\partial \pi} > \frac{\partial P}{\partial k}$). Unlike Cases 1 and 2, the price of flood insurance is not experience-rated. The flood insurance rates set by FEMA are at nearly identical rates before and after each flooding event. Therefore, the change in the implicit marginal price is purely associated with the change in the individuals' subjective assessment of flood risk.

3 Data

Floodplain maps Using geographic information system (GIS), I match all properties to their flood zone. Current floodplain maps (officially "Digital Flood Insurance Rate Maps") are downloaded as state-level National Flood Hazard Layer (NFHL) from FEMA's Flood Map Service Center. For historical floodplain maps, I obtained Q3 Flood Data from FEMA[5], the first digitization of floodplain maps. They were initially produced in 1996 and updated through 1998. For the counties that have had two updates since 1998 (one update between Q3 and the current flood maps), I acquired the second flood maps from the county offices in Kentucky or from FEMA historical raster files. Each property was overlaid on both the current and historical flood maps and assigned one of two conditions for each time period: in a Special Flood Hazard Area (SFHA, equivalent to the 1% floodplain) or outside the floodplain. Figure 3 shows the 70 studied counties.

Real estate data Property sales and characteristics data are sourced from Zillow's ZTRAX database. I matched each recorded sales event in the transaction table to property attribute information in the assessor table. I include the records in Kentucky from January 2005 to October 2021. The dataset contains the transaction date, sale price, the properties' location, structural characteristics, and residential type (i.e., Single family, condominium, mobile home). Housing prices are converted to 2010 Q1 dollars using the All-Transactions House Price Index for Kentucky (KYSTHPI) from the U.S. Federal Housing Finance Agency. I remove outliers with prices below $10,000 or with prices above 100 million dollars. I constructed geographic variables for each property: the distance to the nearest waterbody using the National Hydrography Dataset (NHD) from the United States Geological Survey (USGS)[6] and the distances to the boundaries of current and historical floodplains.

Table 1 provides summary statistics for property and neighborhood characteristics. The average sale price of the properties is $170,000 and houses inside a floodplain are sold $40,000 lower, on average, compared to properties located outside the floodplain. Properties inside the floodplain have larger lot sizes but smaller square footage. Using the tract-level American Community Survey (ACS) 2015-2019 5-year estimates, the houses inside floodplains are more likely to be in neighborhoods that have lower median income and median home value. Among these transactions, 6,539 (1.6%) are always in the floodplain, 1,974 (0.5%) switched into an SFHA, 3,870 (1%) were mapped out of an SFHA and 400,018 (96.9%) are always outside the floodplain. Table 2 reports summary statistics for switchers and non-switchers inside and outside the floodplain.

[5]Additional information on Q3 Flood Data is available here: `https://hazards.fema.gov/femaportal/usercare/guidesAndDocs/Documents/flood_map_svc.htm`

[6]Additional information on the NHD is available here: `https://www.usgs.gov/national-hydrography/national-hydrography-dataset`

Flood event data For large regional floods, I use Presidential Disaster Declaration (PDD) Floods events and NFIP redacted claims as data sources. The PDD system is a formalized process to request and receive federal assistance following large natural disasters. PDD Summaries from FEMA provides information on all ap- proved federal disaster declaration requests, including data on the disaster type, disaster event start and end dates, and affected counties.[7] NFIP redacted claims data[8] provides claim transactions on property type, date of loss, flood zone, and the amount paid on claims. I match the date of loss and the location of each property to the incident period of PDD floods to determine if the flood damage is caused by a large regional flood. Since PDD floods are determined at the county level, not all communities within a county are affected by the flood. I construct a variable to identify which communities in PDD counties are "hit" by each flood. I consider a community to be hit if there are at least $100,000 in building claims linked to the PDD floods within the county subdivision.

4 Empirical Framework

If home buyers update their risk accordingly with new flood maps or flood events, then the price discount should fully capture the risk information. To test the hypothesis, I employ a difference-in-differences (DID) specification with 4 different approaches. Model 1 estimates the effect of floodplain status and flood events on properties that are initially outside the floodplain:

$$ln(P_{ict}) = \beta_1 SwitchIn_{it} + \beta_2 SwitchIn_{it} * Event_{ct} + \beta_3 Event_{ct} + \alpha Z_i + \kappa_{ct} + \epsilon_{ict} \tag{9}$$

Model 2 estimates the effect of floodplain status and flood events on properties that are initially inside the floodplain:

$$ln(P_{ict}) = \beta_4 SwitchOut_{it} + \beta_5 SwitchOut_{it} * Event_{ct} + \beta_6 Event_{ct} + \alpha Z_i + \kappa_{ct} + \epsilon_{ict} \tag{10}$$

[7] Additional information on the PDD data is available here: https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v2

[8] Additional information on the NFIP redacted claims data are available here: https://www.fema.gov/openfema-data-page/fima-nfip-redacted-claims-v1

$ln(P_{i,c,t})$ is log sale price of property i in county c at year t. $SwitchIn_i$ is a dummy variable equal to one if property i is sold and was mapped in SFHA after the flood map updates but outside SFHA before the update. Similarly, $SwitchOut_i$ is a dummy variable equal to one if property i is sold and was mapped out SFHA after the update but was inside SFHA before the update. $Event_t$ is a dummy variable equal to one if a sale occurred after the area has experienced a flood within one or two calendar years and zero if not. Z_i denotes property specific characteristics. κ_{ct} is a fixed effect for each county-quarter, which controls for local market trends. β_1 represents the effect of switching from non-SFHA to SFHA, compared to the properties that are never in the SFHA, and β_4 represents the effect of switching from SFHA to non-SFHA, compared to the properties that are always in the SFHA. β_3 represents the effect of flood events on non-SFHA properties and β_6 represents the effect of flood events on SFHA properties. β_2 isolates the unique effect of the flood event on the properties that are mapped into the floodplain after the map updates and β_5 is the effect of a flood event on the properties that are mapped outside the floodplain after the map updates.

The hypothesis is that being switched into the floodplain will have a larger risk discount for the properties in areas that have experienced a large regional flood within one year of sale compared to areas that have relatively lower flood risk. Individuals may increase their flood risk belief more as they witness both updates and events: $\beta_2 < \beta_1 < 0$. On the other hand, being switched outside the floodplain will have a larger positive impact for the properties that are in relatively lower flood risk areas. Individuals lower their flood risk belief when they are not required to purchase flood insurance and the area did not experience a PDD flood recently: $\beta_4 > \beta_5$.

Model 3 combines (9) and (10) and estimates the effect of changes in floodplain status and flood events on all properties, comparing to the properties that do not have have change in floodplain status:

$$\begin{aligned} ln(p_{ict}) = \delta_1 SwitchIn_{it} + \delta_2 SwitchOut_{it} + \delta_3 SwitchIn_{it} * Event_{ct} + \delta_4 SwitchOut_{it} * Event_{ct} \\ + \delta_5 Event_{ct} + \alpha Z_i + \kappa_{ct} + \epsilon_{ict} \quad (11) \end{aligned}$$

For the properties in areas that did not experience a large regional flood within 1 or 2 years of sale, δ_1 is the effect of switching into floodplain, δ_2 is the effect of switching outside the floodplain, comparing to the houses that did not have a change in flood zone status. Similarly, for the properties in communities that had experienced a PDD flood within 1 or 2 years, δ_3 is the effect of switching into a floodplain, δ_4 is the effect of switching outside the floodplain. This model allows us to look at the effect of updating flood maps in areas that have/have not experienced flooding recently.

5 Empirical Results

Before showing the price effects of both flood map updates and events, I first present the effects of being inside a floodplain. Table 3 presents these results. All specifications include county-by-quarter fixed effects and block fixed effects. Column 1 shows that house prices inside the flood zone are 4.77% lower than those outside. Column 2 shows that the flood risk discount increases to 7.34% if the area has experienced a PDD flood within a year. The increase in discount reflects updated expectations of future flooding and costs related to inundation, such as damage. The estimated flood discount is consistent with previous studies that find marginal impacts of flood risk ranging from 1.1% to 28.7%.

Figure 4 plots the flood zone effects by distance to the flood zone boundary. For properties located in communities with no flooding within a year of sale, prices decrease 4% just inside the flood zone comparing to the ones just outside the flood zone boundary. For properties located in communities with no flooding within a year of sale, prices decrease 8% just inside the flood zone comparing to the ones just outside the flood zone boundary. The hypothesis is that for the houses that gets switched in/out around the flood zone boundary, we would see larger price difference for the areas that had been flooded recently.

Table 4 presents the main estimates corresponding to equations (9), (10), and (11). Model 1 shows the effect of mapping into a SFHA is statistically insignificant for communities that did not experience a PDD flood within a or 2 years. For the houses that switched into a flood zone in areas that have experienced a PDD flood within a year, the housing prices are 6.53% lower than those of houses that stayed outside the floodplain in the communities where there was no PDD flood within a year. This is equivalent to an average decrease of $11,152.02 ($170,781.4*0.0653) in adjusted sale prices. Model 2 shows that the estimated effects of switching out from the floodplain are statistically significant and range from 3.96% for communities that experienced a large flood within a year to 4.09% for communities that experienced a large flood within 2 years. This is equivalent to an average increase of $5,379.51 ($135,846.1*0.0396) to $5,556.11 ($135,846.1*0.0409). Model 3 shows that compared to the houses that did not have a change in flood zone status, houses that are removed from the floodplain experience price increases of 5.17% but the effect of being mapped in is not significant. All models show insignificant effects of switching into a flood zone in areas without a major flood and switching out from a floodplain in areas that experienced one within a year. These findings suggest that home buyers in those areas do not internalize the potential increase/decrease in flood risk solely with the information provided by FEMA's updated maps. The responses to the changes in flood risks are also based on the area's flooding history and the updated flood zones.

Table 5 re-estimates the main specifications from equations (9), (10), and (11) with property fixed effects. By comparing the same property over time, it is possible to control for unobserved, time-invariant characteristics at the individual parcel level that are correlated with flood risk and contribute to price. The drawback of the repeat sales model is that it assumes that there are no structural changes such as physical improvements in the property between sales. The results from Model 3 show that, comparing to the estimates with block fixed effects, the estimates are larger for the effect of switching out and the effect of switching in for recently flooded areas. The comparison indicates that the repeat sales model controls for, at least partly, omitted variable biases stemming from using coarser fixed effects.

6 Heterogeneous effects

Due to the absence of individual home buyer information, I use neighborhood characteristics such as median income and median home value by census tract level to examine if the effects of map updates and flooding events vary by socio-economic status. Table 6 reports the estimates for different neighborhood categories. The effect of switching into flood zones in a flood-prone area is largely driven by the properties in higher income tracts, while properties in lower income communities see significant price increases when mapped out of floodplains in a non flood-prone area. This suggests that communities with lower socio-economic status may have lower salience of flood risk in regards to whether the property is located in a higher risk area. From the summary statistics, houses inside floodplain are likely to be in lower income/home value neighborhoods, home buyers in low socio-economic status communities are more likely to be attracted to properties are removed from a floodplain in a flood-free area. For higher income/home value neighborhoods, the houses that are now at higher flood risk in areas that have been recently flooded are less desirable and the home buyers may taken future flood damage and cost into consideration.

Following Gibson and Mullins (2020), I examine whether the changes in flood risk belief by property values are partially responsible for the observed price changes. They hypothesize that the properties with structural values that are below the flood insurance coverage cap ($250,000) would have smaller effects of switching flood zone status because there is little to no uninsured value and premiums increase slowly in structural value. For the houses above the cap, one would expect larger effects of switching as the prices increase. Figure 5 plots the effects in $75,000 property value bins. The effects of switching out are significant for properties below the cap, which suggests that higher home value buyers do not recognize the reduction in flood risk. However, the interaction effect for switching in and flood events is significant but in the opposite direction. Due to data limitations, I cannot observe the elevation of the building and whether there are structural improvements for reducing flood risk on the property. Home buyers may decrease their risk belief for higher value houses in flood-prone areas as they are more likely to be elevated above the base flood elevation or have flood mitigation on the property.

7 Potential Threats to Identification

A key identifying assumption in a Difference-and-differences model is that treatment and control groups have common counterfactual trends, which means that in the absence of the treatment, the treatment and the control groups would have changed in the same way during the post-treatment period. I test this assumption using event study models. Results are shown in Figure 6. I use 6 months as a time unit, where period 0 represents the 6 months before the flood map updates. The pre-updates period exhibits no significant differential trends. Switching into the flood zone in areas without flooding recently and switching out in areas with flooding have small and insignificant effects on properties before and after flood map updates. Beginning in the one year after the map updates, the price of the properties that are switched into the flood zone in flood-prone are lower.

After 1 year of the updates, properties that are switched out from floodplain in non flood-prone areas increase by 1% in price.

A potential threat to identification is the perfect information assumption of buyers. If buyers are not aware of the flood zone status of properties, the flood risk discount could be only a lower bound. Passed on July 2000, Kentucky Revised Statutes §324.360 requires sellers of single-family residential properties to make certain disclosures to potential buyers. This law included a Seller's disclosure of conditions form and questions regarding the property's flooding history and the flood zone classification. Therefore, I consider the impact of information asymmetry between sellers and buyers to be minimal in the cases of properties in Kentucky and that buyers are well-informed about the flood risk.

A second potential threat is that houses in different flood zones are systematically different and that these differences are time-varying and unobserved by the researcher. If so, using properties from all over the state to construct a counterfactual price path could introduce bias. Therefore, I restrict the sample to the properties within 300 meters of the floodplain boundary and report the estimates in Table 7. The results are similar to the main results in Table 4 with slightly larger effects.

A third potential threat is the endogeneity of flood map updates. If new flood maps were released soon after a flooding event in response to the concern of outdated flood risk information (i.e., the dummy variables of switch in and switch out are correlated with the event dummy variable.), then the estimated coefficient would be biased. Table 8 shows the results of restricting the sample to the counties that had new flood map updates after 6 months of a flooding event. The results are similar to the main results in Table 4 so I consider the bias from the endogeneity issue to be limited.

Due to data availability, a limitation of the study is that it may under/overestimate the risk belief since I do not observe the structural characteristics such as elevation level and flood mitigation. Homeowners and communities can submit Letter of Map Change (LOMC) and Letter of Map Amendment (LOMA) to remove properties from the floodplain if they believe that the property was incorrectly identified. Identifying the precise flood zone status for properties is of interest for future work. Another future avenue of investigation would involve distinguishing inundated structures and "near misses", defined as structures not directly flooded but located inside the floodplain. Previous literature had shown that home buyers perceive inundated properties as being riskier and near misses as relatively less risky. Given these considerations, recovering flooding history and monetary damages may help to better explain the full range of behavioral responses to flood events.

8 Discussion and Conclusion

This study uses a hedonic pricing framework to investigate how the housing market in Kentucky reacts to information from flood map updates provided by FEMA and from flooding events. The paper contributes to the literature by comparing the changes in flood risk belief associated with both flooding history and changes in flood zone status. The results show that housing values decrease by 6% when a property is assigned to a flood zone where the area has experienced a large flood within a year and that housing values increase by 4% when a property is removed from a flood zone where the area has not experienced a large flood recently.

However, the effects are not symmetric. Housing prices do not rebound when removed from a recently flooded area and do not drop when assigned into a flood zone in an area with no flooding within 1 or 2 years. This indicates that the mapping of properties into floodplains is generally not internalized by residents in areas that have not experienced flood events recently, even when facing mandatory flood insurance costs. Similarly, the removal of properties from floodplains in the areas that witnessed flooding recently does not reduce home buyers' flood risk beliefs. These results also provide evidence of heterogeneous responses to flood risk information within different communities and different property values.

The findings imply that individuals' responses to changes in flood risk are based on both recent flooding and flood maps provided by FEMA. The findings suggest some potential improvements to the National Flood Insurance Program. First, FEMA's floodplain maps should provide more detailed and personalized information on flood risk to better serve the housing and insurance markets. FEMA's new flood insurance premium rating system, Risk Rating 2.0, incorporates a wider measurement to calculate each property's individual risk. The additional information should take other relevant factors such as previous flooding events into account. Secondly, FEMA and local governments can increase education and outreach efforts about flood risk and the importance of flood insurance in order to reduce the asymmetric responses by home buyers from different socio-economic statuses. The awareness of differences in the responses/behaviors of home buyers on flood risk is also important for banks and other financial institutes in order to implement appropriate mortgage plans.

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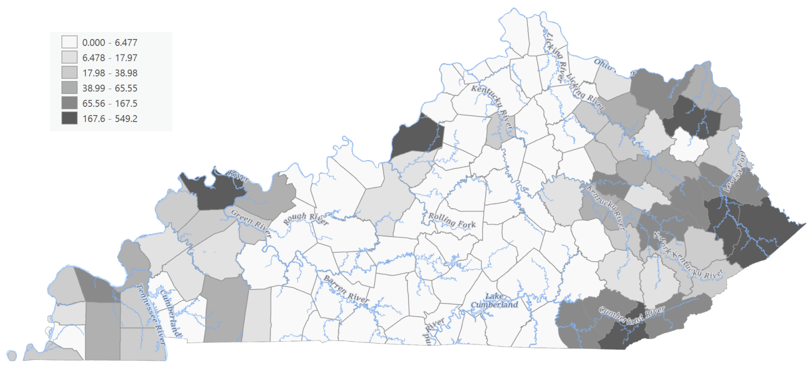
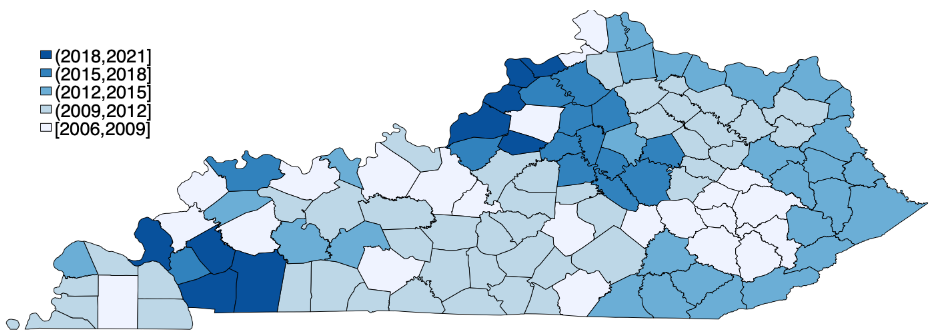
Figures

Figure 1: Ratio of total property damage by floods to from 2000 to 2021 to median home value



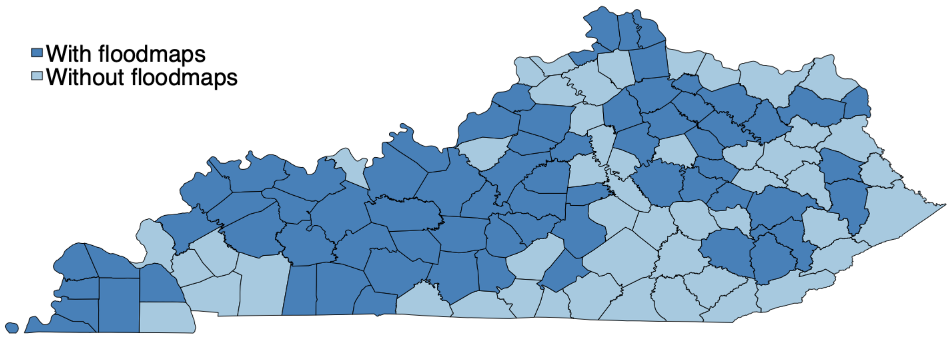
Notes. Property damage data from Storm Data developed by National Weather Service. Estimated median home value from American Community Survey (ACS) 2015-2019 5-year estimate.

Figure 2: Most recent flood maps by year and by county



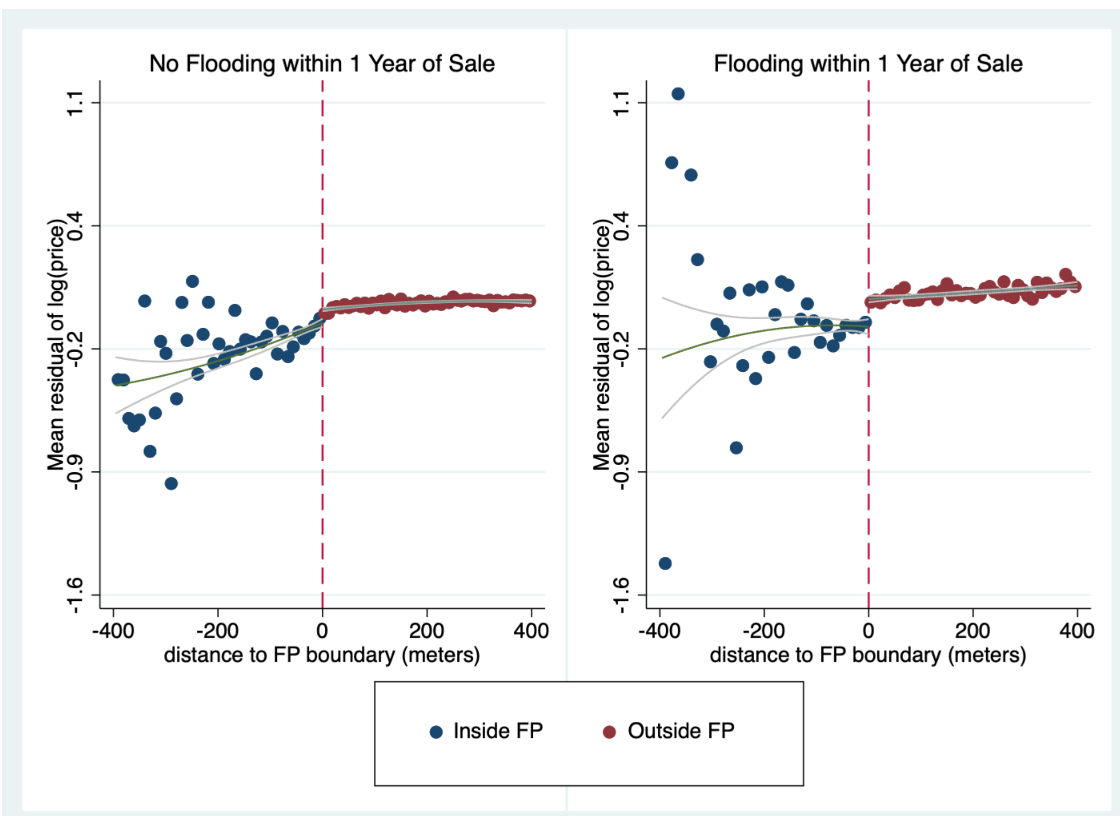
Notes. The figure shows county-level current flood maps' effective dates by year. Flood maps' effective dates are from FEMA flood map service center: https://msc.fema.gov/portal/home

Figure 3: Studied counties



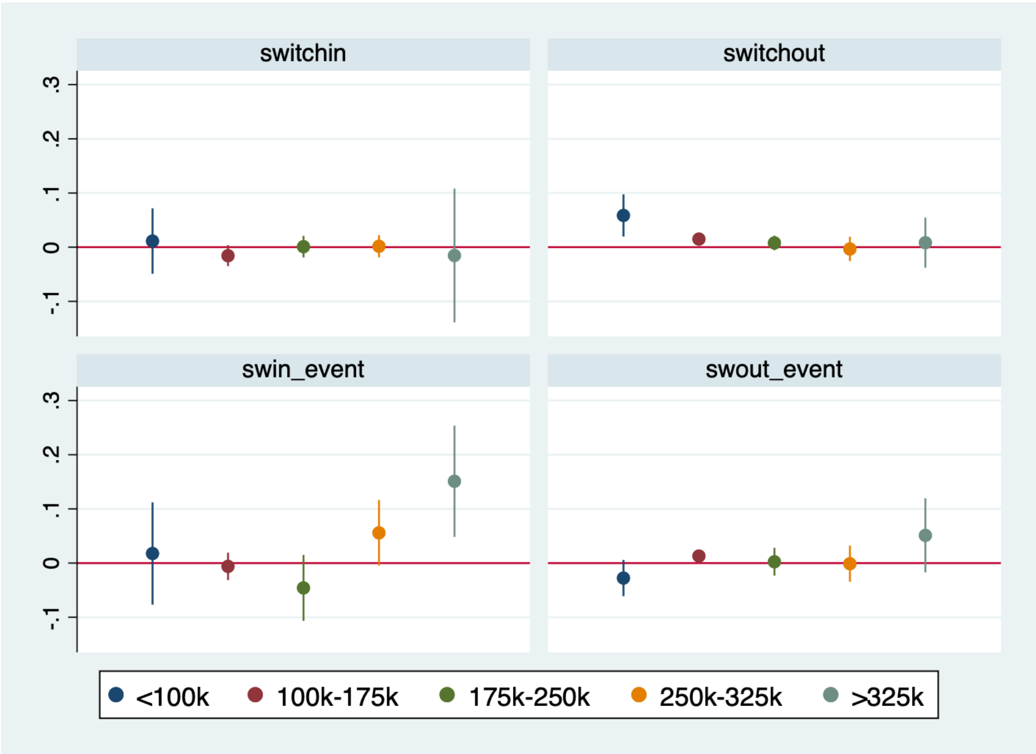
Notes. The figure shows the counties included in the studied sample. Current floodplain maps are from FEMA's Flood Map Service Center. Historical floodplain maps are from the county offices or the historical raster files from FEMA.

Figure 4: Flood zone effects by distance to the flood zone boundary



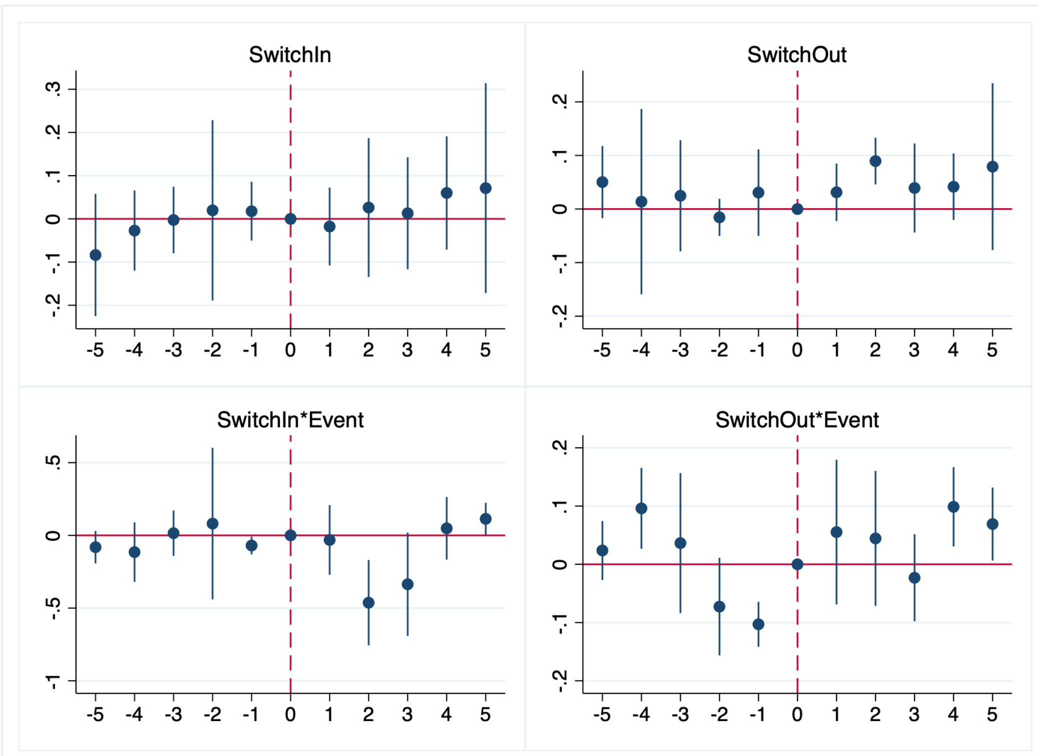
Notes. Log sale prices are regressed on a set of control variables and the coefficients are the average of log prices that belong to different bins by distance to the boundary. All averages are normalized to the bin inside floodplain closest to the boundary.

Figure 5: Heterogeneous effects by property value



Notes. Observations are divided into bins based on the sale prices.

Figure 6: Event study



Notes. Each period is 3 months. Period 0 represents 3 months before the flood map updates. Control groups: 1) properties stayed outside and without a flood within 1 year, 2) properties stayed outside and with a flooding recently, 3) properties stayed inside and without a flooding, and 4) properties stayed inside and with a flooding.

Tables

Table 1: Summary Statistics by flood zone status: SFHA and non-SFHA

	Inside Floodplain		Outside Floodplain	
	Mean	S.D.	Mean	S.D.
Housing Attributes				
Price	126,531	183,193	170,699	400,699
House age when sold	45.91	24.72	39.06	30.69
Bedrooms	1.484	1.570	2.039	1.559
Bathrooms	1.563	0.836	1.886	0.924
Lot size (sqft)	142,152	1.007e+06	114,134	825,556
Square footage	1,482	713.5	1,713	1,548
Dummy for single family	0.941	0.236	0.936	0.246
Dummy for condo	0.0275	0.164	0.0348	0.183
Dummy for mobile home	0.0235	0.151	0.0123	0.110
Dummy for townhouse	0.00840	0.0913	0.0174	0.131
Distance to nearest waterbody (meters)	84.40	100.9	252.9	343.0
Neighborhood Characteristics				
Median income	58,270	29,531	67,849	28,289
Median home value	157,554	99,932	188,179	92,431
Fraction of white	81.20	16.27	81.04	16.99
Fraction in poverty	15.39	9.007	12.36	10.41
Population	4,691	1,749	5,105	2,073
Observations	8,567		408,589	

Notes. Table provides the mean attributes of houses and the neighborhoods inside the floodplain to ones outside the floodplain. Tract-level neighborhood attributes are from American Community Survey (ACS) 2015-2019 5-year estimate.

Table 2: Summary Statistics by flood zone status: switching and non-switching

	Switch In		Switch Out		Always In		Never In	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Housing Attributes								
Price	125,837	216,553	151,290	164,609	126,733	172,309	170,887	402,304
House age when sold	38.53	27.87	34.35	22.36	48.05	23.29	39.10	30.76
Bedrooms	2.055	1.574	1.805	1.620	1.317	1.529	2.041	1.558
Bathrooms	1.553	0.860	1.819	0.839	1.566	0.830	1.886	0.925
Lot size (sqft)	257,955	1.556e+06	184,593	973,907	108,500	775,438	113,452	823,961
Square footage	1,536	652.3	1,591	841.4	1,466	729.6	1,715	1,553
Dummy for single family	0.884	0.320	0.894	0.308	0.957	0.203	0.936	0.245
Dummy for condo	0.0575	0.233	0.0722	0.259	0.0188	0.136	0.0344	0.182
Dummy for mobile home	0.0560	0.230	0.0135	0.116	0.0140	0.118	0.0123	0.110
Dummy for townhouse	0.00259	0.0509	0.0204	0.141	0.0101	0.1000	0.0174	0.131
Distance to nearest waterbody (meters)	71.31	78.89	90.66	92.02	88.20	106.2	254.5	344.1
Neighborhood Characteristics								
Median income	54,806	23,647	60,194	23,212	59,277	30,962	67,923	28,324
Median home value	143,903	73,850	169,987	76,235	161,522	105,994	188,356	92,556
Fraction of white	87.03	11.64	80.11	12.81	79.51	17.02	81.05	17.02
Fraction in poverty	16.55	9.709	13.78	9.536	15.05	8.765	12.34	10.42
Population	4,761	1,807	5,192	1,867	4,671	1,732	5,104	2,075
Observations	1,929		6,638		6,591		401,901	

Notes. Table provides the mean attributes of houses and the neighborhoods inside the floodplain to ones outside the floodplain. Tract-level neighborhood attributes are from American Community Survey (ACS) 2015-2019 5-year estimate.

Table 3: Effect of being in the floodzone on housing price

	(1)	(2) Within 1year	(3) Within 2years
SFHA	-0.0477***	-0.0442***	-0.0419***
	(0.00879)	(0.00980)	(0.0106)
Event		-0.00998	-0.00999
		(0.00932)	(0.00978)
SFHA*Event		-0.0734***	-0.0694***
		(0.0144)	(0.0126)
ln(Lot size)	0.0434***	0.0433***	0.0434***
	(0.00975)	(0.00975)	(0.00975)
ln(Squared Footage)	0.498***	0.499***	0.499***
	(0.0184)	(0.0184)	(0.0184)
squared House age when sold	-1.09e-06	-1.09e-06	-1.09e-06
	(1.02e-06)	(1.02e-06)	(1.02e-06)
Bedrooms	0.00914***	0.00913***	0.00914***
	(0.00314)	(0.00314)	(0.00314)
Bathrooms	0.0897***	0.0897***	0.0897***
	(0.00716)	(0.00716)	(0.00716)
Dummy for single family	0.0898***	0.0898***	0.0897***
	(0.0261)	(0.0261)	(0.0261)
Dummy for condo	-0.0820**	-0.0820**	-0.0820**
	(0.0339)	(0.0339)	(0.0339)
Dummy for mobile home	-0.364***	-0.364***	-0.364***
	(0.0369)	(0.0369)	(0.0369)
ln(Distance to nearest waterbody)	-0.000562	-0.000563	-0.000557
	(0.00233)	(0.00233)	(0.00233)
Constant	7.405***	7.407***	7.408***
	(0.148)	(0.148)	(0.148)
Observations	410,325	410,325	410,325
R-squared	0.692	0.692	0.692
County by quarter FE	Yes	Yes	Yes
Block FE	Yes	Yes	Yes

Notes. Dependent variable is log sale price. Standard errors are stated in parentheses and are clustered at county subdivision level. Price, lot size, squared footage, and distance to nearest waterbody were transformed with natural logs. House age was transformed by squaring the variable. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Effect of map updates and flood events within 1 year or 2 years on housing price

	Model 1		Model 2		Model 3	
	(1)	(2)	(3)	(4)	(5)	(6)
	Within 1year	Within 2years	Within 1 year	Within 2 years	Within 1 year	Within 2 years
SwithIn	-0.0136	-0.0169			-0.0142	-0.0158
	(0.0220)	(0.0231)			(0.0207)	(0.0221)
SwithIn*Event	-0.0653**	-0.0356			-0.0464	-0.0189
	(0.0276)	(0.0311)			(0.0287)	(0.0317)
SwitchOut			0.0396**	0.0409**	0.0517***	0.0588***
			(0.0157)	(0.0194)	(0.0139)	(0.0131)
SwitchOut*Event			-0.0103	-0.0155	0.00776	-0.0165
			(0.0252)	(0.0178)	(0.0184)	(0.0140)
Event	-0.00947	-0.00881	-0.0402*	-0.0486***	-0.0104	-0.0101
	(0.00928)	(0.00990)	(0.0230)	(0.0160)	(0.00936)	(0.00989)
ln(Lot size)	0.0426***	0.0426***	0.0349***	0.0350***	0.0434***	0.0434***
	(0.00983)	(0.00983)	(0.0105)	(0.0104)	(0.00975)	(0.00975)
ln(Squared Footage)	0.500***	0.500***	0.440***	0.440***	0.499***	0.499***
	(0.0184)	(0.0184)	(0.0498)	(0.0498)	(0.0184)	(0.0184)
squared House age when sold	-1.05e-06	-1.05e-06	-2.48e-05***	-2.48e-05***	-1.09e-06	-1.09e-06
	(9.87e-07)	(9.87e-07)	(7.18e-06)	(7.21e-06)	(1.02e-06)	(1.02e-06)
Bedrooms	0.00910***	0.00911***	0.00990*	0.00994*	0.00914***	0.00915***
	(0.00323)	(0.00323)	(0.00561)	(0.00568)	(0.00314)	(0.00314)
Bathrooms	0.0893***	0.0893***	0.0628***	0.0629***	0.0897***	0.0897***
	(0.00726)	(0.00726)	(0.0170)	(0.0168)	(0.00716)	(0.00716)
Dummy for single family	0.0867***	0.0867***	0.221**	0.222**	0.0896***	0.0896***
	(0.0264)	(0.0265)	(0.0949)	(0.0960)	(0.0261)	(0.0261)
Dummy for condo	-0.0848**	-0.0848**	0.141	0.143	-0.0822**	-0.0822**
	(0.0338)	(0.0338)	(0.148)	(0.148)	(0.0339)	(0.0339)
Dummy for mobile home	-0.367***	-0.367***	-0.0559	-0.0484	-0.364***	-0.364***
	(0.0373)	(0.0374)	(0.188)	(0.188)	(0.0369)	(0.0369)
ln(Distance to nearest waterbody)	-0.000593	-0.000589	0.00701	0.00729	-0.000616	-0.000609
	(0.00235)	(0.00235)	(0.0143)	(0.0143)	(0.00234)	(0.00233)
Constant	7.410***	7.411***	7.713***	7.719***	7.406***	7.407***
	(0.147)	(0.147)	(0.368)	(0.368)	(0.148)	(0.148)
Observations	400,042	400,042	9,284	9,284	410,325	410,325
R-squared	0.691	0.691	0.763	0.763	0.692	0.692
County by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Block FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Dependent variable is log sale price. Standard errors are stated in parentheses and are clustered at county subdivision level. Price, lot size, squared footage, and distance to nearest waterbody were transformed with natural logs. House age was transformed by squaring the variable. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of map updates and flood events within 1 year or 2 years on housing price: Repeated sales

	Model 1		Model 2		Model 3	
	(1)	(2)	(3)	(4)	(5)	(6)
	Within 1year	Within 2years	Within 1 year	Within 2 years	Within 1 year	Within 2 years
SwithIn	0.155	0.149			0.0318	0.0382
	(0.127)	(0.125)			(0.0454)	(0.0451)
SwithIn*Event	0.0427	0.0722			-0.0947**	-0.0577
	(0.126)	(0.129)			(0.0374)	(0.0426)
SwitchOut			0.180*	0.180*	0.123*	0.127*
			(0.107)	(0.107)	(0.0646)	(0.0649)
SwitchOut*Event			0.105	0.114	-0.0134	-0.0258
			(0.100)	(0.105)	(0.0255)	(0.0241)
Event	-0.0120	-0.0137	-0.0541	-0.0671**	-0.0131	-0.0153
	(0.0103)	(0.0110)	(0.0343)	(0.0299)	(0.0105)	(0.0110)
squared House age when sold	6.76e-05**	6.66e-05**	9.72e-05*	8.97e-05*	6.73e-05**	6.62e-05**
	(3.05e-05)	(3.06e-05)	(4.91e-05)	(4.97e-05)	(3.04e-05)	(3.05e-05)
Constant	11.59***	11.60***	11.23***	11.26***	11.59***	11.59***
	(0.0695)	(0.0701)	(0.115)	(0.114)	(0.0691)	(0.0698)
Observations	279,928	279,928	5,695	5,695	286,618	286,618
R-squared	0.811	0.811	0.866	0.866	0.813	0.813
County by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Property FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Sample limits to properties sold more than once during the studied period. Dependent variable is log sale price. Standard errors are stated in parentheses and are clustered at county subdivision level. Price, lot size, squared footage, and distance to nearest waterbody were transformed with natural logs. House age was transformed by squaring the variable. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Hetergeneous effect by neighborhood characteristics

	Lower income tracts			Higher income tracts		
	(1)	(2)	(3)	(4)	(5)	(6)
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
SwithIn	-0.0535		-0.0344	0.00667		0.00799
	(0.0394)		(0.0277)	(0.0268)		(0.0252)
SwithIn*Event	-0.0535		-0.000208	-0.0725**		-0.116*
	(0.0557)		(0.0326)	(0.0317)		(0.0663)
SwitchOut		0.0818***	0.0648***		0.0251	0.0396
		(0.0212)	(0.0128)		(0.0223)	(0.0245)
SwitchOut*Event		-0.0110	-0.0260		-0.00702	0.0556*
		(0.0677)	(0.0188)		(0.0303)	(0.0302)
Event	0.0202	-0.0364	0.00248	-0.0137**	-0.0372	-0.0105*
	(0.0142)	(0.0350)	(0.00992)	(0.00630)	(0.0279)	(0.00564)
Observations	94,924	3,092	160,576	304,932	6,099	249,653
R-squared	0.620	0.727	0.628	0.630	0.772	0.608
County by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Block FE	Yes	Yes	Yes	Yes	Yes	Yes
	Lower home value tracts			Higher home value tracts		
	(7)	(8)	(9)	(10)	(11)	(12)
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
SwithIn	-0.0162		-0.0339	-0.0108		0.00375
	(0.0414)		(0.0319)	(0.0235)		(0.0262)
SwithIn*Event	0.00839		-0.0376	-0.0855***		-0.0659*
	(0.0586)		(0.0640)	(0.0278)		(0.0339)
SwitchOut		0.0472***	0.0645***		0.0488**	0.0377*
		(0.0158)	(0.0147)		(0.0228)	(0.0208)
SwitchOut*Event		-0.0221	-0.0125		0.00963	0.0264
		(0.0249)	(0.0220)		(0.0312)	(0.0277)
Event	0.0227	-0.0406***	0.00714	-0.0126	-0.0445	-0.0105*
	(0.0181)	(0.0146)	(0.0107)	(0.00759)	(0.0337)	(0.00608)
Observations	85,341	3,849	132,301	314,600	5,280	277,962
R-squared	0.559	0.582	0.559	0.618	0.775	0.607
County by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Block FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Samples are divided by tract-level median income and median home value in Kentucky from American Community Survey (ACS) 2015-2019 5-year estimate. Dependent variable is log sale price. Standard errors are stated in parentheses and are clustered at county subdivision level. Control variables include lot size, squared footage, house age, number of bedrooms, number of bathrooms, residential type, and distance to nearest waterbody. Price, lot size, squared footage, and distance to nearest waterbody were transformed with natural logs. House age was transformed by squaring the variable. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Robustness: Exclude properties outside 300m of flood zone boundary

	Model 1		Model 2		Model 3	
	(1)	(2)	(3)	(4)	(5)	(6)
	Within 1year	Within 2years	Within 1 year	Within 2 years	Within 1 year	Within 2 years
SwithIn	-0.0249	-0.0265			-0.0235	-0.0240
	(0.0214)	(0.0232)			(0.0202)	(0.0222)
SwithIn*Event	-0.0726**	-0.0482*			-0.0445	-0.0227
	(0.0279)	(0.0283)			(0.0270)	(0.0288)
SwitchOut			0.0451***	0.0473**	0.0625***	0.0693***
			(0.0166)	(0.0204)	(0.0142)	(0.0137)
SwitchOut*Event			-0.00569	-0.00751	-0.000866	-0.0200*
			(0.0252)	(0.0173)	(0.0176)	(0.0117)
Event	-0.00509	-0.00452	-0.0313	-0.00751	-0.00791	-0.00774
	(0.0121)	(0.0101)	(0.0205)	(0.0173)	(0.0120)	(0.0102)
Observations	127,616	127,616	8,874	8,874	137,454	137,454
R-squared	0.694	0.694	0.763	0.763	0.696	0.696
County by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Block FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Sample limits to properties inside 300m of flood zone boundary. Dependent variable is log sale price. Standard errors are stated in parentheses and are clustered at county subdivision level. Control variables include lot size, squared footage, house age, number of bedrooms, number of bathrooms, residential type, and distance to nearest waterbody. Price, lot size, squared footage, and distance to nearest waterbody were transformed with natural logs. House age was transformed by squaring the variable. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Robustness: Exclude counties that had flood maps updated within 6 months after a flooding event

	Model 1		Model 2		Model 3	
	(1)	(2)	(3)	(4)	(5)	(6)
	Within 1year	Within 2year	Within 1year	Within 2year	Within 1year	Within 2year
SwithIn	-0.0179	-0.0216			-0.0164	-0.0186
	(0.0242)	(0.0252)			(0.0228)	(0.0242)
SwithIn*Event	-0.0685**	-0.0327			-0.0455	-0.0153
	(0.0295)	(0.0345)			(0.0310)	(0.0344)
SwitchOut			0.0444***	0.0474**	0.0497***	0.0588***
			(0.0157)	(0.0199)	(0.0146)	(0.0138)
SwitchOut*Event			-0.0169	-0.0171	0.00416	-0.0256
			(0.0272)	(0.0197)	(0.0187)	(0.0160)
Event	-0.00738	-0.00296	-0.0418*	-0.0480***	-0.00839	-0.00454
	(0.0106)	(0.0107)	(0.0239)	(0.0166)	(0.0107)	(0.0108)
Observations	351,225	351,225	8,527	8,527	360,711	360,711
R-squared	0.681	0.681	0.753	0.753	0.681	0.681
County by quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Block FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Dependent variable is log sale price. Standard errors are stated in parentheses and are clustered at county subdivision level. Control variables include lot size, squared footage, house age, number of bedrooms, number of bathrooms, residential type, and distance to nearest waterbody. Price, lot size, squared footage, and distance to nearest waterbody were transformed with natural logs. House age was transformed by squaring the variable. *** p<0.01, ** p<0.05, * p<0.1