Flood Risk and Property Market

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Abstract

Natural disasters including flooding are believed to be more frequent and severe under climate change. Previous research examining the impact of flood risk on housing market usually use hedonic model and thus focus on housing price change. We examine the relationship between flood risk and housing supply, and the impact of controlling housing supply when estimating hedonic price models. We utilize the housing transaction data in Harris County, Texas right before and after the Hurricane Harvey, as well as the detailed damage assessment data by FEMA to examine how housing market respond to extreme events. We find that: (1) Houses in SFHA are more likely to be sold after hurricane Harvey (2) After controlling housing supply factors, we find about 0.5% price drop of houses in SFHA (3) These results are consistent with the explanation that households revise their perceived flood risk right after recent hurricane event and associated house damages.

1 Introduction

According to the latest report by NCEI (2022), U.S. has experienced 310 weather and climate disasters since 1980, and these events in total caused over $2 trillion damages. Among them, flooding has caused the highest damage, which makes it the costliest natural disaster type. NCEI (2022). Climate change is raising the costly flood damage due to both sea-level rise and increasing intensity of hurricane and storms (Cleetus, 2013). This impact is more serious for coastal areas considering higher population density and assets. On average, the annual global flood losses are projected to be increasing to $52 billion by 2050 (Hallegatte et al., 2013).

Given the scale of the problem, it's important to understand how well the market and households are responding to it. How do households update their perceptions of flood risk and how their behaviors would change after receiving new information is a key question to be answered when making policies aiming to promote flood mitigation activities and reduce flood risk. Unfortunately, households usually lack flood risk awareness. Chivers and Flores (2002) shows that most homeowners never realized that their houses are located in high flood risk areas until they made a bid. This asymmetric information between buyers and sellers prevent households from properly internalizing flood risk that they could accept, thus reduces the efficiency of housing market and may also lead to development in flood-prone areas.

The flood risk information of houses are publicly available in the United States. Federal Emergency Management Agency (FEMA) has put in a lot of effort and resources in making the Flood Insurance Rate Map (FIRM) delineating Special Flood Hazard Areas (SFHAs), where on average there is at least 1% chance of being flooded every year. These maps are the primary sources that provide flood risk information to households and communities, However, as already mentioned above, households are unlikely taking fully advantage of this information even when they are buying a house. Hino and Burke (2020) examine the impact of updating of FEMA's flood plain maps and find little evidence that the flood risk information is fully reflected in property market.

Households thus usually receive more salient information about flood risk with lower searching costs in two ways, as is shown in previous research. The first is through Home Seller Disclosure Requirement which requires home sellers disclose whether a house is located in SFHA before closing (Lefcoe, 2004). Researcher have examined how this new information affect home buyers' perceptions. Pope (2008) find that property price declines by 4% in flood zone after the disclosure commenced in North Carolina. Lee (2021) utilize the staggered adoption of the disclosure requirement across 27 states and find similar results that the price of affected properties drop by 4%. The second is through an unexpected shock such as a hurricane. Although economic theory suggests that property located in flood plain would have lower price, the literature shows mixed results: the price discount varies from -75.5% to 61% (Beltrán et al., 2018).

Difference-in-Difference (DID) method has been widely used to identify the impact of amenity change on housing prices (Bishop et al., 2020), including the impact of flood risk on property price. Those research usually use hurricane or flooding event as an exogenous shock, and an interaction term between indicator variables: post period and being located in flood zone (Bin and Polasky, 2004; Hallstrom and Smith, 2005; Kousky, 2010; Atreya et al., 2013; Bin and Landry, 2013). However, one implicit assumption in these studies is that the housing samples used for analysis before and after the exogenous shock are the same, which is unlikely to be true. The houses available on the market could be very different after being hit by a hurricane than before regarding possible damages, renovation, newly built houses, temporarily or permanently removed from the market, and so on. In addition, another aspect of the property market's response to flood risk that's being overlooked is the time that a house needed to be sold, which may reveal the response of housing supply after the shock.

In this paper, we examine how housing market respond to extreme event such as Hurricane Harvey through property duration change in and outside flood zones in Harris County, TX. To answer these questions, we first collect parcel data from Harris County Appraisal District (HCAD) right before Hurricane Harvey. We then extract flood risk information from National Flood Hazard Layer (NFHL) and flood damage assessment data from FEMA. We finally obtain property transaction data in Harris County from

CoreLogic. We attach the flood risk and flood damage data to parcel data in ArcGIS through geological location of each house and then merge with the transaction data through HCAD number. We end up with over 219.720 housing transaction records along with flood risk, flood damage and house characteristics from 2014 to 2020.

We start with a Difference-in-Difference (DID) model and define treatment as being located in SFHA when a house is sold. We find that in general houses take less time (about 1.4%) to be sold in SFHA after Hurricane Harvey. The event study results also show that this effect lasts about two years after the hurricane and return to normal afterwards.

Duration model has been widely used in analyzing different economic questions: limited-entry licensing (Smith, 2004), housing market cycle (Agnello et al., 2015), school absence (Cabus and De Witte, 2015), unemployment duration (Caliendo et al., 2016), credit risk (Watkins et al., 2014; Ben Ayed et al., 2018). However, not much research look at treatment effects in duration models except in labor economics (de Graaf-Zijl et al., 2011; Kyyrä et al., 2013; Schmidpeter and Winter-Ebmer, 2021). We then turn to Cox Proportional Hazard model to examine the same question as both DID and duration models have their drawbacks. Similarly, we find houses are sold faster in SFHA after Hurricane Harvey.

The results from the DID model and duration model both suggest there's a variation of housing supply after the hurricane. To incorporate this supply change, we add three different control variables into price hedonic model, including total number of houses, total number of houses sold, and housing sale probability. We find a short-term price drop of houses about 0.5% to 0.7% after the hurricane.

We conduct the following robustness checks: (1) only use non-damaged houses in SFHA as control group (2) conduct duration analysis using exponential and Weibull model. Our results are generally similar across different specifications.

We then examine the potential mechanism of these temporary effects by further check the impact of damage caused by the hurricane on ownership duration and housing price. We find that both the effects on ownership and housing price are larger for more severely damages houses. The findings in together suggest that households update their perceived flood risks after recent hurricane shock and associated house damages.

The paper proceeds as follows. Section 2 describes background and data. Section 3 lays out the empirical strategy. Section 4 presents the results and section 5 discussed potential mechanism. Section 6 concludes.

2 Background and Data

The two research questions of this paper are: first, to examine the impact of flood risk on housing supply; second, to understand the impact of housing supply on hedonic price model results. To answer these questions, we compile a dataset from different sources including Harris county parcel information, housing transactions, flood risk level, and house-level damage assessment after hurricane Harvey.

2.1 Study Area

Harris county is the largest county in Texas with nearly 5 million population in 2020. Due to the adjacency to the Gulf of Mexico, Harris county, as well as the whole Texas exposed to more hurricanes. On average, Harris county experiences a major flood every two years. Some examples include Tropical Storm Allison in 2001, Hurricane Ike in 2008, and Hurricane Harvey in 2017. Among all those extreme events, Hurricane Harvey is the unique one that never happened in Harris County before. It brought the highest rain amount and widest spatial coverage compared to the recorded United States history Jeff and Steve (2018). In total, Hurricane Harvey caused about 125 billion dollars of damage and ranked as the second costliest hurricane in American history, only after Hurricane Katrina in 2005.

2.2 Parcel Data

The parcel data is collected from Harris County Appraisal District (HCAD), who provides public available data about property information. They usually update the parcel shapefile in October of each year. We use tax parcel shapefile of 2020 as the base data, and link it to property sales data through the HCAD account number. This data set is used as a snapshot of all available homes for sale before the Hurricane Harvey. The shapefile provides the detailed location information of each parcel, which we use later to determine their flood risk and damage status. We use the 2020 parcel shapefile because it includes all houses built in or before 2020, which covers the whole study period of this research.

2.3 Flood Risk and Damage Data

We extract the latest Special Flood Hazard Area (SFHA) map of Harris county from National Flood Hazard Layer(NFHL) geospatial database from FEMA Flood Map Service Center [1] and overlay it with parcel map mentioned above to identify whether a parcel is located in SFHA, areas with 1% of annual probability of being flooded on average.

Starting October of 2012, FEMA worked with a group of modeling and risk analyst experts from the National Hurricane Center (NHC) and the US Geological Survey to evaluate damage to houses caused by Hurricane Sandy (McCoy and Zhao, 2018). The so-called FEMA's Modeling Task Force (MOTF) combine both inundation measurements with aerial images to generate real point-damage estimates of structures (Ortega and Taşpınar, 2018). They conduct similar assessment for Hurricane Harvey in 2017. These data also include latitude and longitude of each structure assessed, which enables us to overlay it with our parcel data and determine houses that were actually affected or not affected by the hurricane. Figure 1 shows an example of how the damaged houses are distributed across flood zones. As shown in figure 1, houses located in SFHA are more likely to experience flood damage. About 21.3% of houses in SFHA are damaged, while only 3.6% of houses in NSFHA are damaged. Although the percentage of damaged houses in NSFHA is smaller, the total number of houses affected in NSFHA is much larger than those in SFHA: 60.3% of them are in NSFHA.

[1] The NFHL database is available at `https://hazards.fema.gov/femaportal/NFHL/searchResulthttps:/hazards.fema.gov/femaportal/NFHL/searchResult`.

2.4 Property Transactions Data

The property transaction data is from CoreLogic, which contains data on home sales in Harris County, TX between March 1990 and April 2021. The data includes a unique identifier for each house, HCAD account number, sales date and price, property characteristics such as year a house was built, number of bedrooms and bathrooms, square footage, and number of stories, property location information such as zip code and census tract number. The 2016 parcel data mentioned before is then linked to the property transaction data through the HCAD account number.

We apply several filters to clean the property transactions data: (1) restrict the data to single-family home (2) drop records with missing house key characteristics such as year built (3) drop records without sale price or sale date (4) drop transactions with sale date prior to built year (5) drop observations with sale price less than 1% ($37504.38) or greater than 99% ($100,000,0). We end up with 219,720 transaction records from 2011 to 2020. We drop property transactions in 2021 because it's not complete - only includes sales for the first quarter.

The start date of this study is set at September 13th. 2014, 6 years after Hurricane Ike, in order to minimize the potential lasting impact of it and 3 years before Hurricane Harvey so that there are enough transactions for analysis before the storm. The end date of the study is the date of the last transaction in the dataset: March 26th, 2021. The property transaction data provides all recorded transactions of each house from 2011 to 2021. We calculate the duration of ownership as number of days between the latest sale date and the second latest sale date, whenever available. For those houses only sold once during this period, the duration is the number of days between the latest sale date and the earlier date of either the date it was built or the start date.

Table 1 provides summary statistics of the data. The average ownership duration is 1,064 days (about 2.92 years), with the maximum duration being 2,386 days (6.54 years). The mean sale price is $244,704, with average house age being 31.26 years. About 10.6% of houses in our sample are located in 100-year flood zone, and 5.8% of all sold houses are damaged because of Hurricane Harvey.

3 Empirical Model

The first thing needs to point out is that we are not trying to model the developers' decision of building new houses. Houses built in different year may either subject to stricter building code standards and households may value house characteristics differently over time, especially after a hurricane. These house attributes may be unobserved and affect how fast a house could be sold. We are not assuming that every existing house is always for sale. In other words, the housing supply consists of (1) the housing stock change - houses built before the study period and on the market (2) new houses built each year during the study period. We start with the sample that only includes houses built in or before 2014 to avoid composition effect. We focus on number of houses built before 2014 and actually sold on the market during our study period and discuss the impact of newly built houses later. Based on the data we have, we use the length of time between sales of a house (ownership duration) to approximate the supply change of the housing market. As the ownership duration decreases after the hurricane indicates more houses are available on the market, i.e. higher supply. The ownership duration is used here because it reflects the variation in housing stock, as well as the speed of housing market adjustment in response to specific events (Archer et al., 2010).

Another issue worth mentioning is that as previous research show, housing price and time on the market (TOM) of a house are usually simultaneously determined as home sellers solving their utility maximization problem under certain constraints (Turnbull and Zahirovic-Herbert, 2012). This co-determination complicates empirical analysis since they are determined by the same set of factors, which cause under-identification issue. To solve this problem, several solutions have been brought up, although there is no unanimous or perfect method (Benefield et al., 2012). A lot of those studies use two-stage least squares (2SLS) approach to solve the endogeneity problem, which essentially requires finding a instrumental variable (Ferreira and Stacy Sirmans, 1989,?; Knight, 2002; Hayunga and Pace, 2019). The main challenge here is that there's no direct test of exogeneity of these proposed instruments, thus the benefits of using instrument variable are not guaranteed (Irwin and Wolf, 2022).

We choose to model housing price and ownership duration separately in this paper for two reasons (Irwin and Wolf, 2022). First, the key question we are trying to answer here is not the relationship between housing price and housing liquidity. Instead, we want to focus on the housing supply dynamics after Hurricane Harvey and its impact on hedonic price model results. In fact, previous literature show sale price and TOM are usually negatively correlated, but the results are very mixed (Benefield et al., 2014; Dubé and Legros, 2016). Second, most of those research mentioned above focus on TOM, which is different from ownership duration that's used as an indicator of housing supply variation in this paper. Although the correlation between sale price and TOM may cause a problem, TOM is relatively short compared to the whole length of ownership, which may alleviate the potential issue. We solve this problem explicitly later by including price in the ownership duration model.

3.1 Ownership Duration Model

3.1.1 Difference-in-Difference Model

Our goal here is to examine the impact of flood risk on housing supply after Hurricane Harvey. We start with defining "treatment" here as being located in SFHA. At this point, we don't differentiate houses that experienced damage or not due to Harvey and use all houses outside of SFHA as control group. One common challenge here is that the houses in and outside of SFHA are different in terms of characteristics. We include block group fixed effects to make them as comparable as possible (Ortega and Taşpınar, 2018). Thus, we are comparing the responses of households living in areas with high and low flood risk, as reflected in the sales rate of houses. To examine how house duration change after Hurricane Harvey, we estimate the following model:

$$log(T_{ijt}) = \alpha_j + \beta_1 \text{Post}_t + \beta_2 \text{Floodzone}_i + \beta_3(\text{Post}_t * \text{Floodzone}_i) + \gamma_i X_{ij} + \delta_t + \epsilon_{ijt} \quad (1)$$

where $log(T_{ijt})$ is the log of number of days of property i located in census block group j before it's sold in time t. $Post_t$ is a dummy variable and equals to 1 if a house is sold after Hurricane Harvey. $Floodzone_i$ is a dummy variable indicating whether a house is located in 100-year flood zone. β_3 is the coefficient we are interested of, which measures the effect of flood risk on property duration. X_{it} includes property characteristics such as number of bedrooms, square footage, year built and so on. α_j is neighborhood fixed effect capturing unobserved time-invariant factors that affect all properties within a census block group. δ_t is time fixed effect drawn at both year and month level, which controls for the seasonality of housing market. ϵ_{ijt} is the idiosyncratic error.

Our identification assumption here is that, the time needed before a house is sold are the same for houses located in and outside 100-year flood zone before Hurricane Harvey. We estimate the following model to examine the parallel trend assumption, as well as the existence of dynamic treatment effect:

$$log(T_{ijt}) = \alpha_j + \sum_{l=-3}^{4} \mu_l Floodzone_{i,t}^l + \gamma_i X_{ij} + \delta_t + \epsilon_{ijt} \tag{2}$$

where $Floodzone_{i,t}^l$ is a set of indicators and equal to 1 if a house is sold l years away from Hurricane Harvey (positive/negative l refers to transactions occurred after/before 2017). μ_l measures the dynamic impact of flood risk on ownership duration over time. The rest of the model is similar to equation 1.

3.1.2 Duration Model

One drawback of the fixed-effect model above is that it assumes that the possibility of ownership termination is time-invariant over time. this is unrealistic considering that the situation a household facing is changing over time, especially if they experienced extreme event such as Hurricane Harvey. A hazard-based model could be used to solve this problem but also comes with costs (Irwin and Wolf, 2022). Adding fixed-effects into duration model could cause incidental parameters problem and lead to biased estimates (Lancaster, 2000), thus researches using duration model often don't include fixed-effects or only include higher spatial scale fixed-effects (Smith, 2004; Archer et al., 2010; Irwin and Wolf, 2022).

We start with a estimating the classic Kaplan-Meier estimator of the survival function. To be specific, the K-M estimator of the probability that that a house is sold beyond time t is given by the product of survival probabilities in time t and previous periods:

$$S_t = \prod_{j=1}^{t}[(r_j - d_j)/r_j] \tag{3}$$

We then apply the proportional hazard model, a semi-parametric approach introduced by Cox (1972) to estimate the causal effect of flood risk on rate of housing sales. Compared to weibull and exponential models with additional functional form restrictions, the proportional hazard model makes no assumptions about the baseline hazard function (Cox, 1975; Deng et al., 2003). Let T_i be a random continuous variable measuring the days from being on the market until being sold of a house i. Then the hazard rate of a house being sold is modeled using a mixed proportional hazard specification:

$$\theta_i(t|x, d, v_i) = \lambda_i(t)exp(x\beta_i + \delta_1 d + v_i) \tag{4}$$

where $\lambda_i(t)$ is the baseline hazard rate that only depends on t. d is the treatment variable and equals to 1 if a house is located in 100-year flood zone when it's sold, and 0 otherwise. x includes all time-invariant housing characteristics. v_i are the unobserved characteristics of each house.

3.2 Housing Price Model

We then turn to the impact of flood risk on housing price. While hedonic model is widely used for evaluating the marginal willingness to pay (MWTP) for environmental amenities, it suffers from the potential omitted variables bias (Kuminoff et al., 2010). As suggested by Kuminoff et al. (2010), researchers could get more accurate estimates by including spatial fixed effects and temporal controls, and applying more quasi-experiment design (such as DID). For example, Ortega and Taşpınar (2018) use city block fixed effect to guarantee the comparability between control and treatment groups. Another example is that Bernstein et al. (2019) use a set of interacted fixed effects to help identify the impact of sea level rise on housing price.

Similarly to equation 1, we use a common difference-in-difference model to examine the impact of flood risk on housing price.

$$log(P_{ijt}) = \alpha_j + \beta_1 \text{Post}_t + \beta_2 \text{Floodzone}_i + \beta_3 (\text{Post}_t * \text{Floodzone}_i) + \gamma_i X_{ij} + \theta_j Supply_{jt} + \delta_t + \epsilon_{ijt} \tag{5}$$

where $log(P_{ijt})$ is the log of transaction price of property i located in census block group j in time t. $Post_t$ is a dummy variable and equals to 1 if a house is sold after Hurricane Harvey. All the other variables are the same as before. What differentiates our model from previous research is that we try to mitigate the potential omitted variable issue by controlling for supply side factors. We use both several ways to capture the supply side variation $Supply_{jt}$ in equation 5: (1) the total number of houses in a block group in each year (2) the total number of houses sold in a block group in each quarter (3) the probability of a house being sold in a block group in each quarter.

4 Results

4.1 Ownership Duration Model Results

We start by showing the general trend in housing sales before and after Hurricane Harvey. For each quarter, we calculate the housing sale probability by dividing total number of house sold in each block group by the total number of houses in that block group. We plot the housing sale probability against quarters in figure A1. It's clear that the housing market in Harris county is very seasonal with transaction peaks in the second and third quarters each year before the hurricane. We observe a drop in housing sales in quarter 3, 2017 when the hurricane happened, while slightly higher sale probability in the following two quarters. Next we examine the differences of sale probabilities in and outside flood zone, where we define a block group as being in SFHA if any part of the block group is in SFHA. Figure A2 shows that in general the probability of house sale in SFHA and

NSFHA have similar trend before Hurricane Harvey, and usually houses in flood zone are less likely being transacted. Similar to the pattern shown in figure A1, we observe a sharp decline in house sales in the third quarter in 2017 for both SFHA and NSFHA. While the probability that a house being sold in SFHA is higher in the following year. We find that being in SFHA reduces the probability of house sale before Hurricane Harvey, while it turns to a short-term opposite impact after the hurricane.

4.1.1 DID Model Results

Table 2 reports the results of estimating equation 1. The dependent variable is the natural log of number of days before a house is sold. We first notice that the estimated coefficients in column (1) and (2) are similar after adding log of sale price as control variable, which indicates that the potential correlation between sale price and ownership duration is not a big issue here. Table 2 shows that in general there's no difference regarding ownership duration of houses in and outside SFHA. However, after Hurricane Harvey, we find a 1.4% of reduction in ownership duration.

We then turn to the results of event study estimates. Figure 2 shows the results of estimating equation 2. The estimated coefficients of event year indicator, as well as 95% confidence interval (shaded area) are plotted against event year. None of the estimated coefficients for pre-Harvey years are statistically different from zero, indicating that parallel trend likely holds. The figure shows that Hurricane Harvey causes decrease in ownership duration by about 2.1% and 1.6% in 1 and 2 years after the event, respectively. This effect on ownership duration tends to end and reduce to -0.5% in year 3 and no longer significant. All the coefficients afterwards are not significantly different from 0. The results from DID model and event study model suggests that Hurricane Harvey leads to a temporary faster sale of houses in SFHA, compared to houses outside of SFHA.

4.1.2 Duration Model Results

Figure 3 lots the baseline hazards by estimating equation 3 for our treatment variable $Post * SFHA$. We see a clearly faster sell rate for houses in SFHA after Harvey and then slows down and gradually becomes similar to houses in NSFHA. Figure 3 suggests that there's differences in and outside of SFHA regarding how households respond to Hurricane Harvey.

Table 3 reports the results of estimating equation 4. The dependent variable is the number of days before a house is sold. Similarly, column (2) only differs from column (1) by including sale price as control variable. The hazard ratio estimated for $Post*SFHA$ in both columns are greater than 1, indicating that the likelihood of being sold for houses in SFHA is higher by about 4.7% after Hurricane Harvey. Most of the coefficients estimated for house characteristics are also expected. For example, houses that are older and with more stories take longer to sell, while houses with more bedrooms, more bathroom, with pool take less time to sell.

4.2 Housing Price Model Results

We now turn to the price dynamics after hurricane Harvey. The results of estimating equation 5 are reported in table 4. The dependent variable is the natural log of housing transaction price. The first thing to mention is that the potential correlation between sale price and ownership duration is not a big issue here, according to the similar results shown in column (1) and (2). The estimated coefficients of $Post*Floodzone$ are negative but not significant. From column (3) to (5), we control for supply side of the property market by adding different variables. *# of Total houses* is the total number of houses in a block group in each year, which is used to represent the maximum number of houses that could be on the market. *# of houses sold* is total number of houses sold in a block group in each quarter, and *Sale probability* is the probability of a house being sold in a block group in each quarter. The latter two variables are used to capture the supply of property market at a more detailed time scale level. We find significant housing price decline of 0.5% to 0.7% after Hurricane Harvey.

We then turn to the results of event study estimates. We estimate equation 2 but now replace the dependent variable with natural log of housing price. The event study results are shown in figure 4. All estimated coefficients for pre-Harvey indicators are not different from zero. We only observe a very small price decline (about 0.9%) in year 1 after the hurricane. All the coefficients afterwards are not significantly different from 0. The results from DID model and event study model suggests that Hurricane Harvey leads to a short-term price decline of houses in SFHA, compared to houses outside of SFHA.

4.3 Robustness Check

Our current model assume that only houses in SFHA are treated after Hurricane Harvey, while in reality houses in NSFHA may also experience damages. In other words, houses on NSFHA may also expose to the effect of the hurricane and these households may change their behavior accordingly regarding selling their houses. To alleviate this concern, we now drop houses that are damaged in NSFHA and only keep non-damaged in NSFHA as control group and re estimate equation 1 and 4. The results are reported in table B1 and B2. The results are similar to the baseline results above.

Another concern regarding the CPH model is that we couldn't control for time trend or spatial trend (as all houses are in the same county). We also use exponential and Weibull duration model as alternatives of CPH model, although they impose additional assumptions about the baseline hazard function Cameron and Trivedi (2005). We re-estimate model 4 using an exponential and Weibull model and report the results in table B3. Similarly, we find that houses in SFHA are more likely (about 2.8% - 4.2%) to be sold after Hurricane Harvey.

5 Potential Mechanisms

In the previous section, we show that Hurricane Harvey leads to faster housing transactions in SFHA (about 1.4%) along with price decline (about 0.7%). We also find that these effects are both temporary considering that the impact on duration lasts for two years, while the impact on housing price lasts only for one year. Combining these results regarding ownership duration and housing price, they are consistent with a slight supply surplus. Although we couldn't say much about demand-side adjustment, our results show that maybe the supply-side change is greater than the demand-side change.

The supply increase here is not because of newly-built houses since we excluded them from the sample. It's more likely because more people would like to sell their houses after the hurricane, especially those houses being damaged. We first test this by examining the impact of flood damage on ownership duration and housing price. We estimate the following event study specification:

$$log(T_{ijt}) = \alpha_j + \sum_{l=-3}^{4} \mu_l Damaged_{i,t}^{l} + \gamma_i X_{ij} + \delta_t + \epsilon_{ijt} \tag{6}$$

The only difference from equation 2 is that the treatment is that a house experiences damage because of Hurricane Harvey. The dependent variables are the natural log of number of days before a house is sold and the natural log of housing price. The results are reported in figure 5 and figure 6, respectively. Figure 5 shows that houses suffered damage from the hurricane take about 0.3% shorter time to be sold in the following year after the event, and about 0.3% and less time to be sold in the second year. Figure 6 shows that houses damaged after the hurricane experience about 0.2% price decline in the year right after the hurricane. These results may indicate that the faster housing sales and price drop in SFHA is driven by those houses that are damaged during the hurricane.

To further examine this hypothesis and check the heterogeneous impact of different levels of damage of houses, we re-estimate the equation 6, while now we replace *Damaged* with *Damage*0, *Damage*1, and *Damage*2, which equals to 1 if the damage level is "affected", "minor damage", "major damage or destroyed", respectively. Figure 7, 8, and 9 represent the results of the dynamic impact of flood damage on ownership duration. We find that houses experienced minor damage experience are sold about 5.2% faster after the hurricane, while houses that are seriously damaged or destroyed are sold about 3.3% to 8.4% faster in the three following years after the hurricane. Similarly, figure 10, 11, and 12 represent the results dynamic impact of flood damage on housing price, respectively. We find that housing price dropped by about 1.4% to 2%, 2.5%, and 4.7% after the hurricane as the severity of house damage escalated.

We observe similar patterns of the impact of flood damage on ownership duration and housing price. Houses that survived the hurricane and are only "affected" don't see any change on ownership duration and the minimum price drop if they are sold. While houses that experience more serious damage are more likely to be sold after the hurricane on a lower price. For those houses that are seriously damaged or destroyed, we find the largest impact of flood damage on ownership duration and housing price. On one hand, it takes time for households to apply and receive funds from government or insurance company for house repair or rebuild, and it takes even longer for reconstruction if they houses are destroyed. On the other hand, if households want to sell their severely damaged houses without rebuilding their houses after the hurricane, they'll have to accept a much lower selling price.

As shown in previous research, households tend to neglect flood risk if it only happens at relatively low probability Botzen and van den Bergh (2012). Then households depend on shocks of recent flood events to update their belief of local flood risk regarding their properties, and causing either price drop of houses or increase up-take of flood insurances Atreya et al. (2013); Gallagher (2014). Our empirical results are consistent with these results. Hurricane Harvey, as an extreme event, may have served as strong reminder of future flood risk and lead to more households' willingness to sell their houses at a lower price Ortega and Taṣpınar (2018).

6 Conclusion

We provide two major findings in this paper. First, we find a significant increase of housing supply in SFHA after hurricane Harvey, as is reflected in the higher probability of house sale in SFHA. Second, we also show that it's important to control supply side factors when estimating a hedonic price model. Our results show that, on average, houses in SFHA are sold 1.4% faster and about 0.5% to 0.7% cheaper after the hurricane. These impacts are both temporary and lasting only up to 3 years.

We further examine the potential reasons of these results by estimating the impact of damage caused by flooding. Our results are driven by houses that experienced damages during the hurricane, and these effect are larger for more severely damaged houses. The most likely explanation of our findings is that households update their belief of future flood risk and are more willing to sell their houses at a lower price after the hurricane. These results together suggest that a recent disaster, as well as associated physical damage to houses may increase households' perceived flood risks.

Collectively, our findings suggest that households may use hurricane experience as new information source regarding their decision of living in or out of SFHA. The short-term effects indicate a fast recovery of the property market from the shock of hurricane, which may be because of frequent previous flooding experiences since Texas is one of the states that are most directly impacted by hurricanes.

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Main Tables

Table 1: Summary Statistics

Variable	N	Mean	St. Dev.	Min.	Max.
Price ($)	219,720	243,814	129,766	38,688	1,037,850
Days	219,720	1,041	671	1	2,301
Flood zone	219,720	0.104	0.306	0	1
Damaged	219,720	0.058	0.234	0	1
Area (acre)	219,720	0.204	0.275	0.013	25.06
No. of bedroom	219,720	3.436	0.737	1	32
No. of bathroom	219,720	2.621	0.887	1	16
Lot size (sqft)	219,720	2,214	808	252	13,503
Has garage	219,720	0.951	0.216	0	1
Has pool	219,720	0.128	0.334	0	1
No. of story	219,720	1.476	0.593	1	5
No. of building	219,720	1.012	0.151	1	16
House age	219,720	29.99	21.05	0	154

Notes: This table reports the summary statistics of the whole sample at transaction unit. Days is the number of days before a house is sold. Flood zone equals to 1 if a house is located in 100-year flood zone.

Table 2: The Effect of Flood Risk on Rate of Sale

	Log(Days)	
	(1)	(2)
Log(price)		-0.113***
		(0.006)
Flood zone	0.001	0.001
	(0.003)	(0.003)
Post*Flood zone	-0.014***	-0.014***
	(0.004)	(0.004)
House age	-0.001***	-0.001***
	(0.000)	(0.000)
Area	0.009***	0.015***
	(0.002)	(0.003)
Lot size	0.0000**	0.00001***
	(0.00000)	(0.00000)
No. of bedroom	-0.001	-0.001
	(0.001)	(0.001)
No. of bathroom	-0.003***	-0.002
	(0.001)	(0.001)
No. of story	0.0004	-0.002*
	(0.001)	(0.001)
Has pool	0.0003	0.005***
	(0.002)	(0.002)
Has garage	0.006*	0.007**
	(0.003)	(0.003)
Year	Yes	Yes
Month	Yes	Yes
Block group	Yes	Yes
R^2	0.794	0.794
N	219,720	219,720

Notes: This table reports results from equation 1. The dependent variable is log of the number of days before a house is sold. Flood zone equals to 1 if a house is located in 100-year flood zone. Post equals to 1 if a house is sold after Hurricane Harvey. Robust standard errors clustered at census block group level are in parentheses. Asterisks indicate the following: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 3: The Effect of Flood Risk on Rate of Sale - Duration Model

	Days	
	(1)	(2)
Log(price)		0.689***
		(0.014)
Flood zone	1.018	1.022
	(0.010)	(0.010)
Post	0.032***	0.032***
	(0.010)	(0.010)
Post*Flood zone	1.047*	1.049*
	(0.014)	(0.014)
House age	0.996***	0.996***
	(0.0001)	(0.0001)
Area	0.972***	0.982***
	(0.008)	(0.008)
Lot size	1.000***	1.000***
	(0.0000)	(0.0000)
No. of bedroom	1.006	0.992*
	(0.004)	(0.004)
No. of bathroom	1.013**	1.031***
	(0.005)	(0.005)
No. of story	0.954***	0.962***
	(0.005)	(0.005)
Has pool	0.994	1.010
	(0.007)	(0.007)
Has garage	0.933***	0.950***
	(0.010)	(0.010)
N	219,720	219,720
R^2	0.614	0.615

Notes: This table reports results of estimating equation 4. Hazard Ratio are reported. The dependent variable is number of days before a house is sold. Flood zone equals to 1 if a house is located in 100-year flood zone. Post equals to 1 if a house is sold after Hurricane Harvey. Robust standard errors clustered at census tract level are in parentheses. Asterisks indicate the following: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 4: The Effect of Flood Risk on Housing Price

	Log(Price)				
	(1)	(2)	(3)	(4)	(5)
Log(days)		-0.028***			
		(0.001)			
Flood zone	0.002	0.003	0.004	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Post*Flood zone	-0.005	-0.005	-0.007**	-0.005	-0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
# of Total houses			-0.00002***		
			(0.00000)		
# of Houses sold				0.0001	
				(0.0001)	
Sale probability					0.691***
					(0.088)
House age	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Area	0.058***	0.058***	0.058***	0.058***	0.058***
	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
Lot size	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
No. of bedroom	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No. of bathroom	0.017***	0.016***	0.017***	0.017***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No. of story	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Has pool	0.042***	0.042***	0.042***	0.042***	0.042***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Has garage	0.016***	0.017***	0.016***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Year	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes
Block group	Yes	Yes	Yes	Yes	Yes
R^2	0.736	0.737	0.737	0.736	0.737
N	212,199	212,199	212,199	212,199	212,199

Notes: This table reports results from equation 5. The dependent variable is log of price when a house is sold. Flood zone equals to 1 if a house is located in 100-year flood zone. Post equals to 1 if a house is sold after Hurricane Harvey. Robust standard errors clustered at census block group level are in parentheses. Asterisks indicate the following: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Main Figures

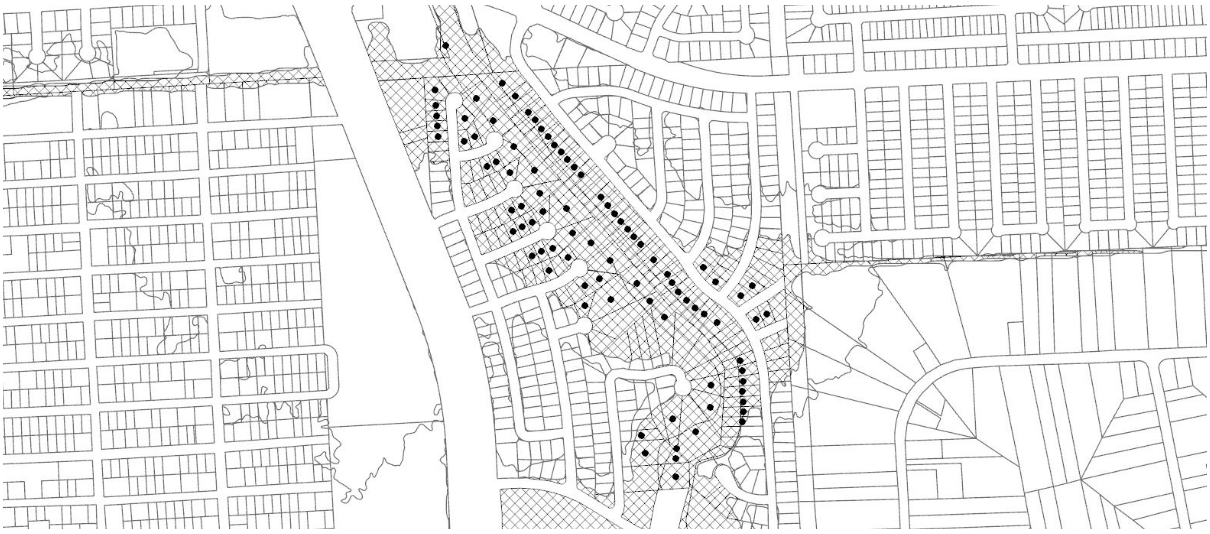

Figure 1: Illustration of Parcel Map, Flood Zone and Flood Damage

Notes: Each polygon in the figure indicates a parcel. The polygons in crosshatch are in SFHA. The black dots indicate damaged buildings.

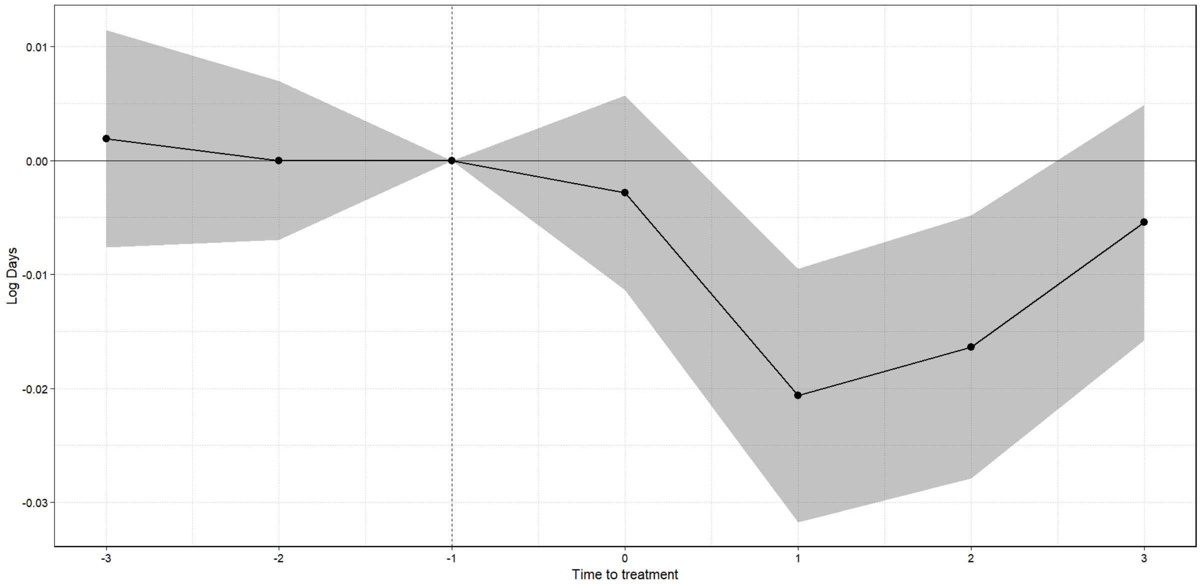

Figure 2: The Impact of Flood Risk on Ownership Duration

Notes: This figure shows the results of event study estimating equation 2. The dependent variable is the natural log of number of days before a house is sold. The coefficient for the year before treatment is normalized to zero. The gray-shaded area show the 95% confidence interval. Standard errors are clustered at census tract level.

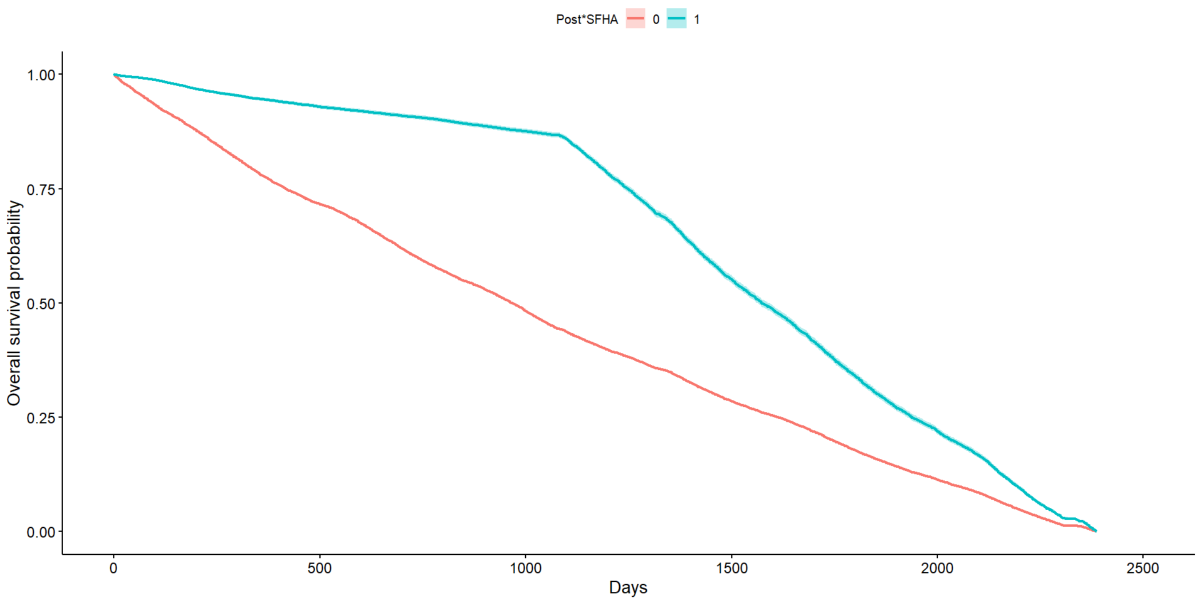

Figure 3: Kaplan-Meier Curve- SFHA v.s. NSFHA Post Harvey

Notes: This figure shows the result of Kaplan-Meier survival curve estimating equation 3. X axis is the number of days before a house is sold. Y axis is the overall survival rate.

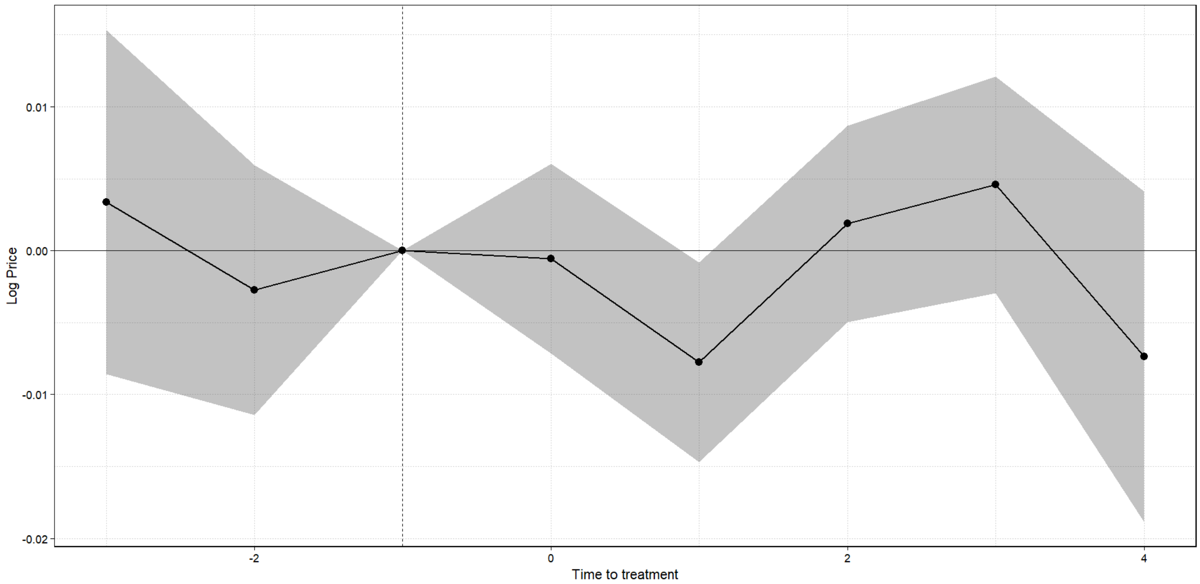

Figure 4: The Impact of Flood Risk on Housing Price

Notes: This figure shows the results of event study estimating equation 2 while the dependent variable is the natural log of housing price. The coefficient for the year before treatment is normalized to zero. The gray-shaded area show the 95% confidence interval. Standard errors are clustered at census tract level.

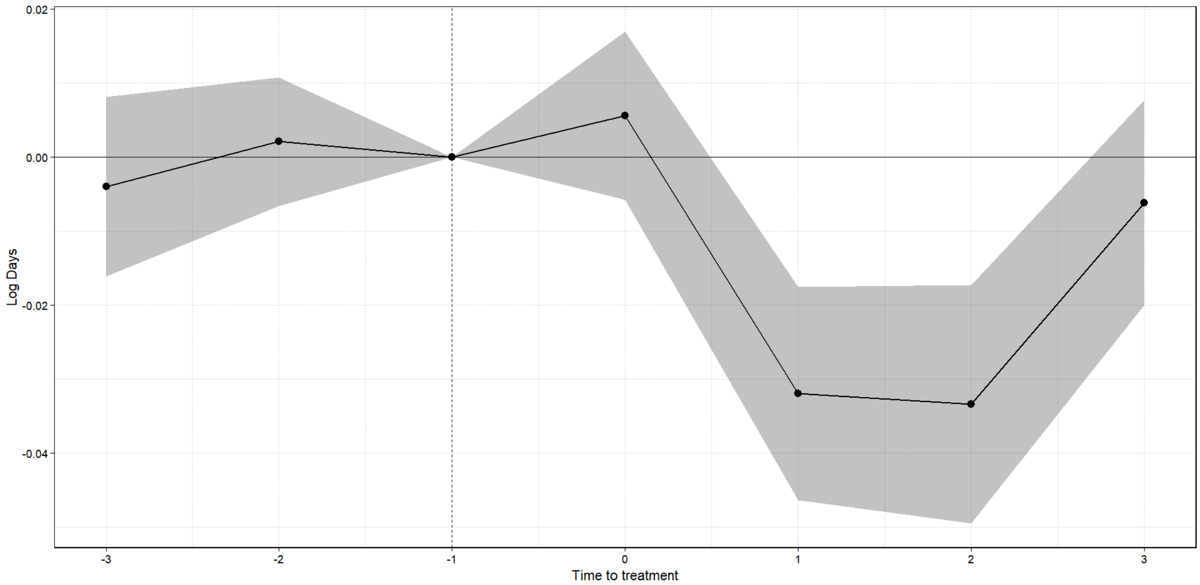

Figure 5: The Impact of Flood Damage on Ownership Duration

Notes: This figure shows the results of event study estimating equation 6. The dependent variable is the natural log of number of days before a house is sold. The coefficient for the year before treatment is normalized to zero. The gray-shaded area show the 95% confidence interval. Standard errors are clustered at census block group level.

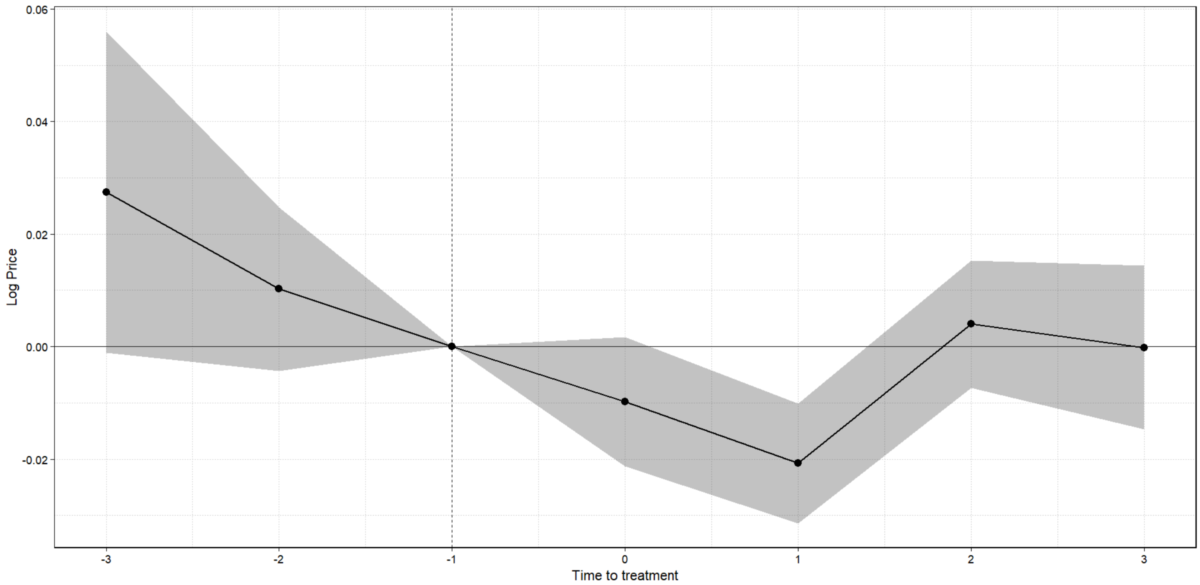

Figure 6: The Impact of Flood Damage on Housing Price

Notes: This figure shows the results of event study estimating equation 6. The dependent variable is the natural log housing transaction price. The coefficient for the year before treatment is normalized to zero. The gray-shaded area show the 95% confidence interval. Standard errors are clustered at census block group level.

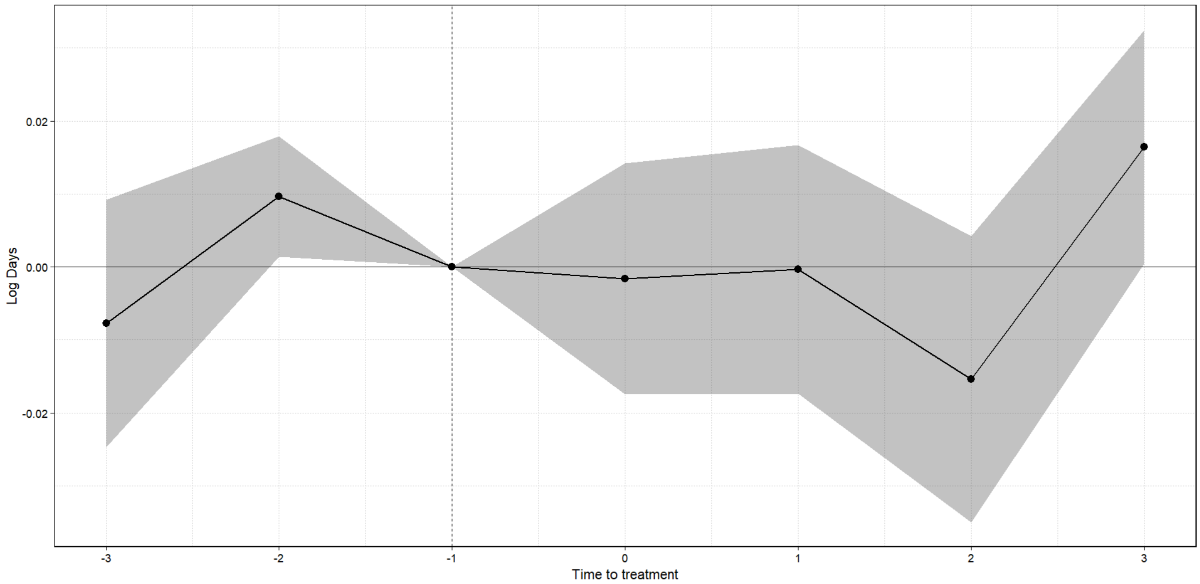

Figure 7: The Impact of Flood Damage on Ownership Duration - "Affected"

Notes: This figure shows the results of event study estimating equation 6. The dependent variable is the natural log of number of days before a house is sold. The coefficient for the year before treatment is normalized to zero. The gray-shaded area show the 95% confidence interval. Standard errors are clustered at census block group level.

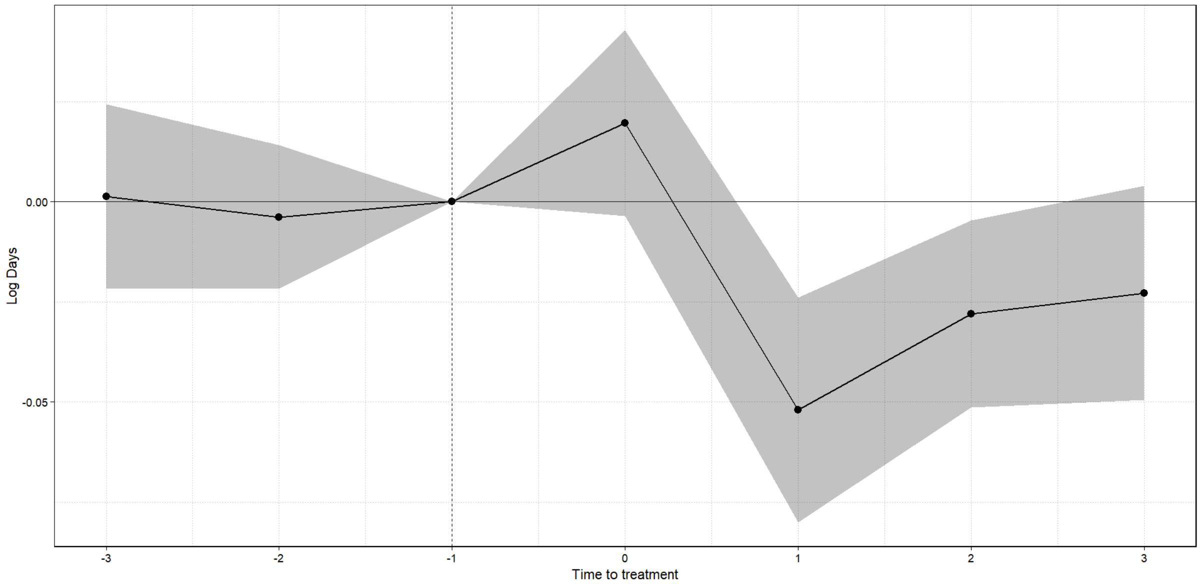

Figure 8: The Impact of Flood Damage on Ownership Duration - "Minor Damage"

Notes: This figure shows the results of event study estimating equation 6. The dependent variable is the natural log of number of days before a house is sold. The coefficient for the year before treatment is normalized to zero. The gray-shaded area show the 95% confidence interval. Standard errors are clustered at census block group level.

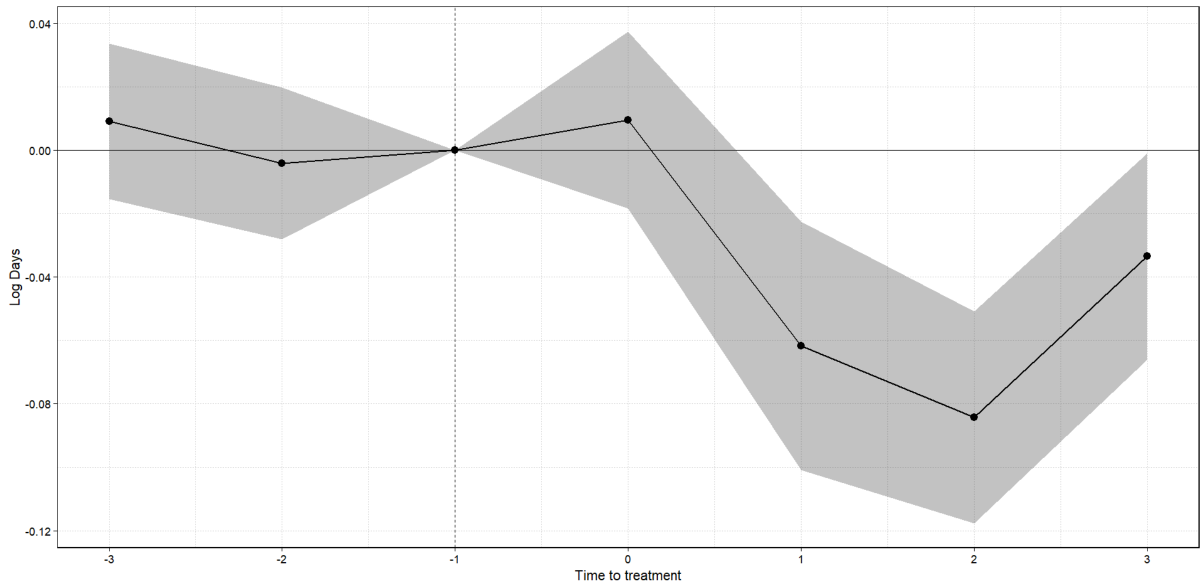

Figure 9: The Impact of Flood Damage on Ownership Duration - "Major Damage or Destroyed"

Notes: This figure shows the results of event study estimating equation 6. The dependent variable is the natural log of number of days before a house is sold. The coefficient for the year before treatment is normalized to zero. The gray-shaded area show the 95% confidence interval. Standard errors are clustered at census block group level.

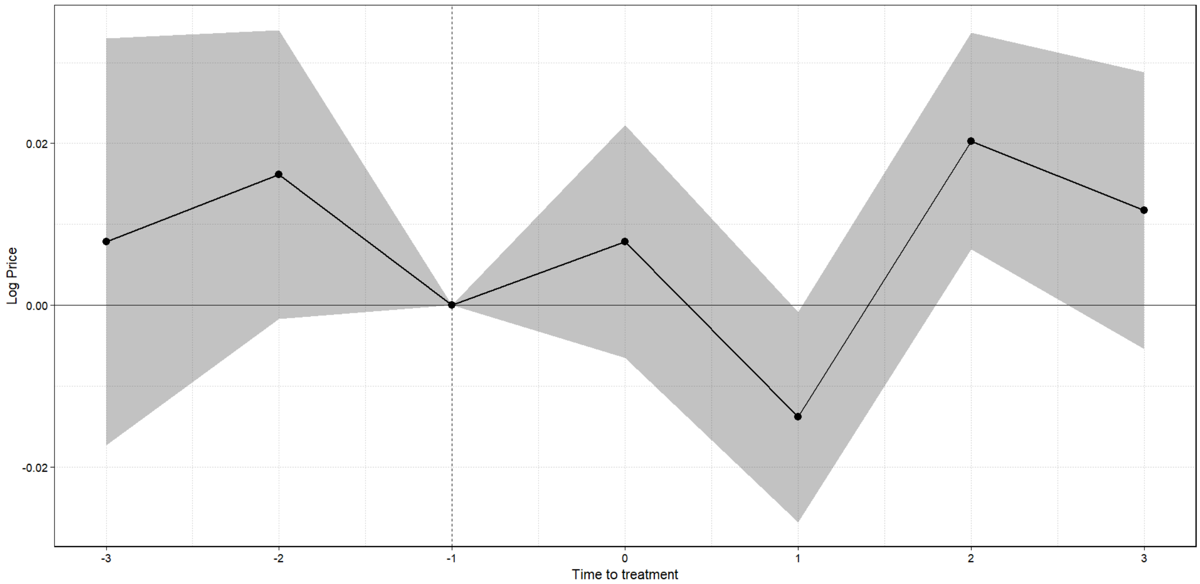

Figure 10: The Impact of Flood Damage on Housing Price - "Affected"

Notes: This figure shows the results of event study estimating equation 6. The dependent variable is the natural log of housing transaction price. The coefficient for the year before treatment is normalized to zero. The gray-shaded area show the 95% confidence interval. Standard errors are clustered at census block group level.

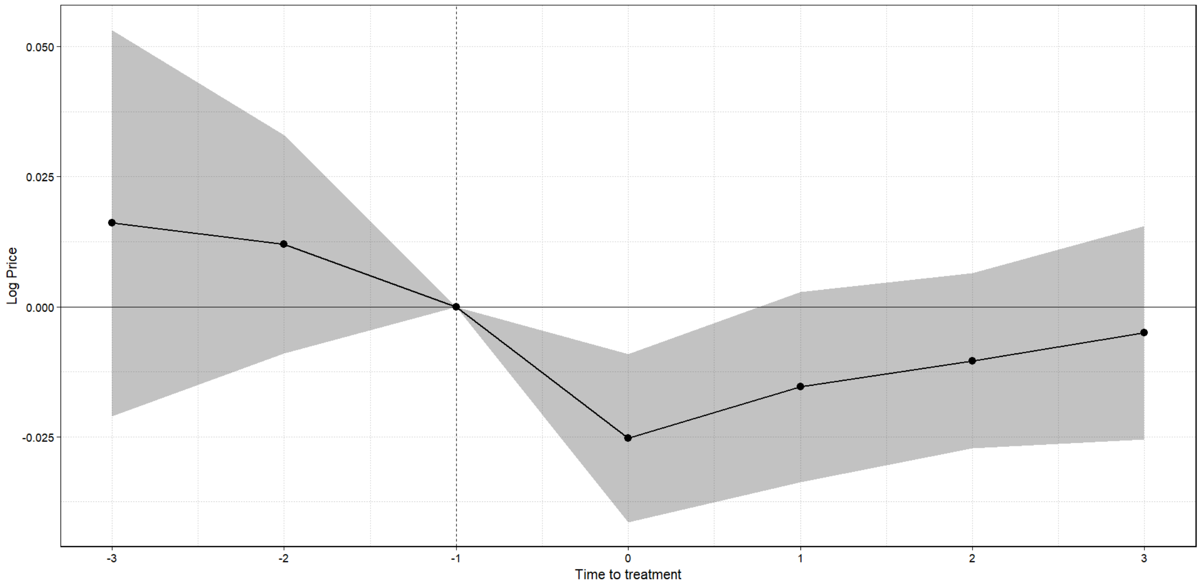

Figure 11: The Impact of Flood Damage on Housing Price - "Minor Damage"

Notes: This figure shows the results of event study estimating equation 6. The dependent variable is the natural log of housing transaction price. The coefficient for the year before treatment is normalized to zero. The gray-shaded area show the 95% confidence interval. Standard errors are clustered at census block group level.

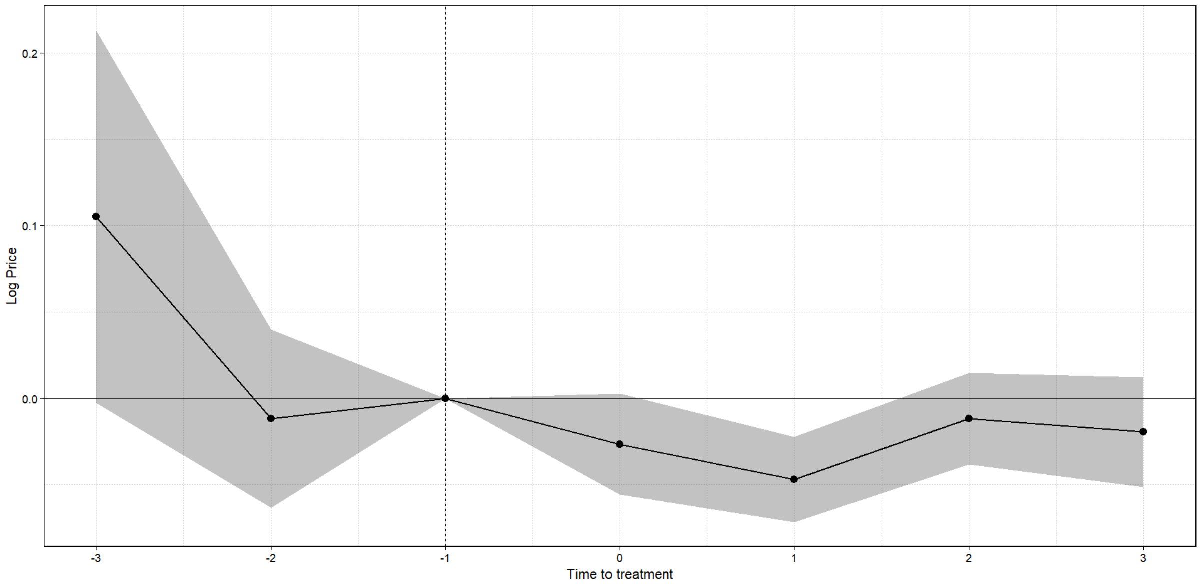

Figure 12: The Impact of Flood Damage on Housing Price - "Major Damage or Destroyed"

Notes: This figure shows the results of event study estimating equation 6. The dependent variable is the natural log of housing transaction price. The coefficient for the year before treatment is normalized to zero. The gray-shaded area show the 95% confidence interval. Standard errors are clustered at census block group level.

A Appendix A Additional Figures

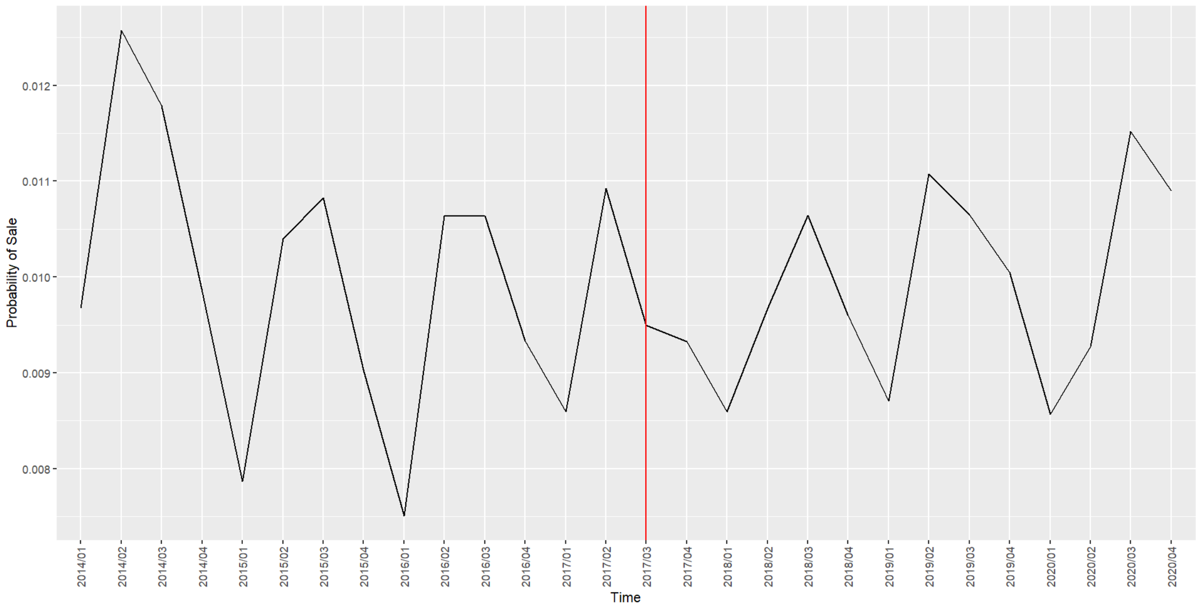

Figure A1: Sale Probability over Time

Notes: This figure shows the average housing sale probability by block group over time.

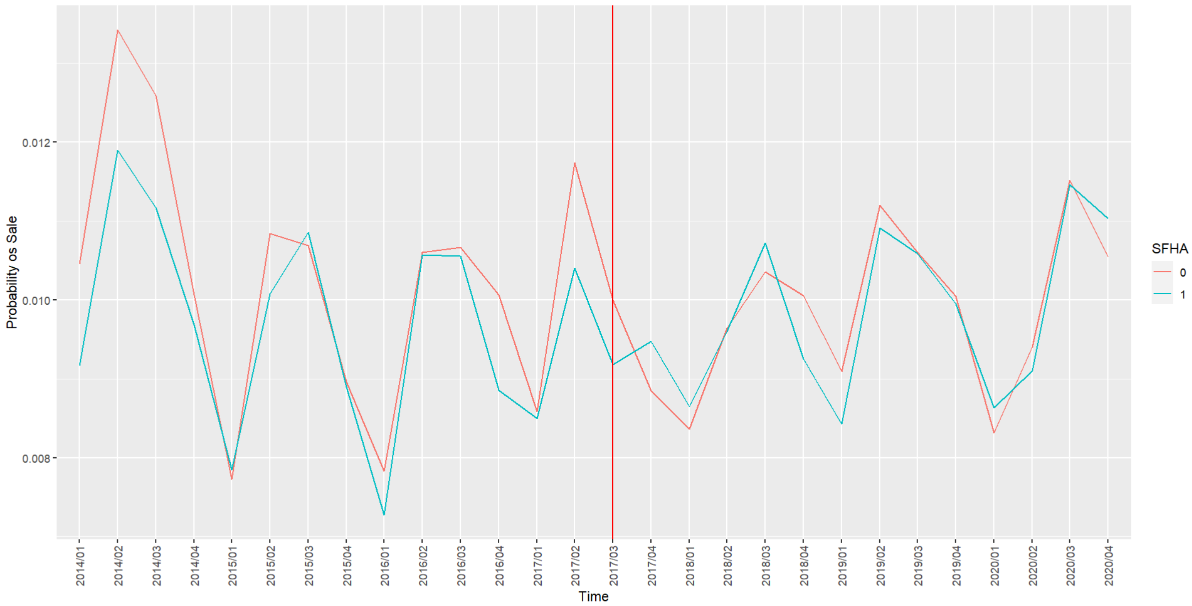

Figure A2: Sale Probability by SFHA

Notes: This figure shows the block group level housing sale probability by SFHA status over time.

B Appendix B Additional Tables

Table B1: The Effect of Flood Risk on Rate of Sale

	Log(Days)	
	(1)	(2)
Log(price)		-0.112***
		(0.006)
Flood zone	0.002	0.002
	(0.001)	(0.001)
Post*Flood zone	-0.014***	-0.014***
	(0.004)	(0.004)
House age	-0.001***	-0.001***
	(0.000)	(0.000)
Area	0.009***	0.015***
	(0.002)	(0.002)
Lot size	0.0000**	0.00001***
	(0.000)	(0.000)
No. of bedroom	-0.001	-0.001
	(0.001)	(0.001)
No. of bathroom	-0.004***	-0.002
	(0.002)	(0.002)
No. of story	0.0004	-0.002**
	(0.001)	(0.001)
Has pool	0.001	0.005***
	(0.002)	(0.002)
Has garage	0.005***	0.007***
	(0.003)	(0.003)
Year	Yes	Yes
Month	Yes	Yes
Block group	Yes	Yes
R^2	0.794	0.795
N	212,199	212,199

Notes: This table reports results from equation 1 using non-damaged houses in NSFHA as control group. The dependent variable is log of the number of days before a house is sold. Flood zone equals to 1 if a house is located in 100-year flood zone. Post equals to 1 if a house is sold after Hurricane Harvey. Robust standard errors clustered at census block group level are in parentheses. Asterisks indicate the following: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table B2: The Effect of Flood Risk on Rate of Sale - Duration Model

	Days	
	(1)	(2)
Log(price)		0.694***
		(0.014)
Flood zone	1.018	1.022
	(0.010)	(0.010)
Post	0.032***	0.032***
	(0.011)	(0.011)
Post*Flood zone	1.050**	1.051**
	(0.014)	(0.014)
House age	0.996***	0.997***
	(0.0001)	(0.0001)
Area	0.971***	0.981***
	(0.008)	(0.008)
Lot size	1.000***	1.000***
	(0.0000)	(0.0000)
No. of bedroom	1.007*	0.993
	(0.004)	(0.004)
No. of bathroom	1.013**	1.030***
	(0.005)	(0.005)
No. of story	0.957***	0.965***
	(0.005)	(0.005)
Has pool	1.009	0.988
	(0.007)	(0.007)
Has garage	0.933***	0.940***
	(0.011)	(0.011)
N	212,199	212,199
R^2	0.615	0.617

Notes: This table reports coefficient estimates of equation 4 using non-damaged houses in NSFHA as control group. Hazard Ratio are reported. The dependent variable is the number of days before a house is sold. Flood zone equals to 1 if a house is located in 100-year flood zone. Post equals to 1 if a house is sold after Hurricane Harvey. Robust standard errors clustered at census tract level are in parentheses. Asterisks indicate the following: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table B3: The Effect of Flood Risk on Rate of Sale - Exponential Weibull Model

	No. of Days before Sold	
	Exponential	Weibull
Flood zone	1.009	1.010
	(0.010)	(0.005)
Post	0.324***	0.137***
	(0.004)	(0.002)
Post*Flood zone	1.028**	1.042***
	(0.014)	(0.007)
Dist. to water	1.000*	1.000**
	(0.000)	(0.000)
House age	0.998***	0.996***
	(0.000)	(0.000)
Area	0.997	0.996
	(0.004)	(0.002)
Lot size	1.000	1.000
	(0.0000)	(0.0000)
No. of bedroom	1.004	1.004
	(0.004)	(0.002)
No. of bathroom	1.003	1.006
	(0.005)	(0.002)
No. of story	0.977***	0.967***
	(0.005)	(0.002)
Has pool	0.988*	0.992
	(0.007)	(0.003)
Has garage	0.958***	0.943***
	(0.010)	(0.005)
Constant	0.002***	0.000***
	(0.016)	(0.008)
N	232,343	232,343
R^2	0.612	0.614

Notes: This table reports results of estimating equation 4 using exponential and Weibull model. Hazard Ratio are reported. The dependent variable is number of days before a house is sold. Flood zone equals to 1 if a house is located in 100-year flood zone. Post equals to 1 if a house is sold after Hurricane Harvey. Robust standard errors clustered at census tract level are in parentheses. Asterisks indicate the following: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.