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# Informed by wet feet: How do floods affect property prices?

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**Abstract**

We investigate the effect of multiple flood events on property prices in Zurich canton of Switzerland. By merging property transaction data with records from universal and mandatory building insurance, we are able to identify the effect of the informational content of floods separately from the damage caused. Our rich data allows us to control for a wide range of housing characteristics, thus reducing the bias from unobserved heterogeneity that routinely plagues hedonic regressions. We find that houses located in flood hazard zones sell at a discount relative to houses located outside, despite the presence of mandatory insurance that covers most (but not all) costs. Providing flood hazard information increases the value of houses that are assigned a low risk. Last, we look at the effect of floods on property prices and find that in the aftermath of flood events, properties that narrowly escaped damage were sold at a significant discount relative to houses located out of harm's way. This pure information effect decays shortly.

*Keywords*: Flood risk; hedonic pricing; amenity value; availability bias; spatial hedonic model

*JEL codes*: Q51, Q54, R21

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# 1 Introduction

Floods are among the most important natural disasters worldwide. The largest flood impacts tend to be located in coastal areas as a result of hurricanes or tsunami events, but flooding is also important in inland areas. About 21 million people worldwide are affected by river floods each year. Due to climate change and socio–economic developments, the number of affected people is predicted to increase to 54 million by 2030 as the surface temperature continues to rise (Luo et al., 2015; Willner et al., 2018). Switzerland, which is the focus of this paper, is no exception. In 2015, the damage to private property, infrastructure, forestry and agriculture caused by floods, debris flows, landslides and rock falls amounted to CHF 135 million, 92 percent of which resulted from floods (Hilker et al., 2009).[1]

Flood damages depend on the affected housing stock. For this reason, it is important that flood risk be reflected in current and future housing development, for example in the form of building restrictions or insurance mandates, but also in market prices. In this paper, we examine the effect of flood events on housing prices in Switzerland. Our data allow us to control for a wide range of housing characteristics, predicted flood risk and actual damages due to river floods in the years 2007–2019 in the canton of Zurich. We find that flood events cause a drop in the price of (spared) houses located in the proximity of damaged houses, relative to comparable houses located further away. This implies that flood events contain information that causes home buyers to update their expectations about flood risk.

A number of previous hedonic pricing studies estimated the effect of sea floods on housing values. Table A.1 in the Appendix presents a comprehensive overview of the related literature. Most of the studies focus on the USA that impose mandatory flood insurance via the National Flood Insurance Program for properties located in a 100–year floodplain.[2] A recent meta-analysis by Beltrán et al. (2018b) finds an average price discount of 4.6% for houses located in an inland 100–year floodplain, which increases to 6.9% in the aftermath of a flood. The situation in Switzerland differs from the US context as home owners are required by law to buy a flat-rate building insurance, which covers the full (estimated) monetary damages caused by flooding at a price that does not depend on the risk of flooding associated with the location of the building. As

[1] The Swiss Franc, or CHF, is currently at par with the US dollar.

[2] For a survey of the older literature, see Boyle and Kiel (2001). Examples of more recent studies are Daniel et al. (2009), Atreya and Ferreira (2015) and Bakkensen and Barrage (2017).

a result, homeowners in safe areas cross-subsidize houses located in risky areas, for example near rivers or in the mountains. This socialized insurance should, in principle, remove any price differentials due to flood risk with the exception of uninsurable costs such as the possibility of death, injury or being displaced, damage to municipality infrastructure, transactions costs or the loss of personal items with sentimental value. This makes it more difficult to identify a risk-related price differential in the Swiss real estate market. On the other hand, the presence of a socialized insurance scheme means that we have accurate information about flood damages (via insurance claims) and that there is no unobserved price component due to insurance fees (as the price is the same for everyone). Despite the insurance scheme, we find a price discount for houses located in flood-prone areas. This discount is temporary in nature and occurs in the aftermath of floods.

Most hedonic price models of flood risk estimate the price differential between houses based on cross-sectional variation.[3] However, the identification of the flood risk-component in such a setting may suffer from omitted variable bias and from measurement error bias, because flood risk tends to be imprecisely measured. The first contribution of our paper lies in improving the estimate of the risk differential by including additional information about transacted houses that are typically not available in most data sets. Furthermore, we use detailed hazard maps as our ex-ante measure of risk. These maps assign flood risk to individual properties and should thus reduce the measurement error problem that has plagued previous studies. Controlling for attributes and flood risk zone, we find no stable flood risk differential in housing prices.

Another way to identify the impact of floor risk on property prices is the use of a Difference-in-Difference (DiD) spatial hedonic model framework to exploit an exogenous variation in risk at a given location.[4] Most of the previous DiD studies use flood zones to estimate price differentials for floodplain location before and after a flood (as the *ex-ante* risk of flooding usually does not change discretely). The treatment group typically consists of houses located within a particular floodplain, whereas the respective control group is located outside (see, e.g., Bin and Polasky, 2004; Daniel et al., 2007; Atreya and Ferreira, 2012; Bin and Landry, 2013; Atreya et al., 2013a; Hill, 2015). This design avoids the omitted variable bias, but the interpretation of the DiD-effect is not

[3] See for example Barnard (1978); Skantz and Strickland (1987); Shilling et al. (1989); MacDonald et al. (1990); Fridgen et al. (1999); Shultz and Fridgen (2001); Morgan (2007)

[4] An example is Davis (2004), who focuses on house prices in a county where residents had recently experienced a severe increase in pediatric leukemia. Housing prices are compared before and after the increase with a nearby county acting as a control group. Billings and Schnepel (2017) estimate the benefits of lead-paint remediation on housing prices adopting a DiD estimator that compares values among remediated properties with those for which an inspection does not identify a lead paint hazard.

obvious as it could be caused by at least three mechanisms: First, the price decrease (if any) could be due to the flood damage itself, provided that damages are sufficiently widespread (Atreya and Ferreira, 2015). Second, insurance premia could increase for houses located in the flood zone due to a permanent upward adjustment of the expected flood risk by the insurance provider. And third, home buyers could adjust their expectations about flood risk if a flood event increases the salience of a risk (Hallstrom and Smith, 2005; Kellens et al., 2013; Burningham et al., 2008). For example, price effects in the US disappeared around six years after Hurricane Floyd (Bin and Landry, 2013) and eight to nine years after the flood of 1994 in Georgia (Atreya et al., 2013b).[5]

Without additional information about insurance premia and actual damages, these channels cannot be distinguished from each other. Given our context of socialized building insurance, however, we can rule out any changes in insurance premia. Furthermore, the universal coverage leads to complete claims information on all houses. This allows us to identify the properties that were damaged by the flood and differentiate them from houses that were merely at risk. Our DiD estimator of "near–miss" events on prices of non-damaged properties in close proximity to recorded damages relative to prices of properties located further away thus identifies the pure effect of informational updating in the wake of a flood. This is the second contribution of our paper. To our knowledge, there exist no previous studies that separately identify actual damages from informational updating as a consequence of flood events. Some previous papers have used information about the geographic extent of the flood to proxy for unobserved damages. Atreya and Ferreira (2015), Beltrán et al. (2019) and Beltrán et al. (2018a) compare properties that were actually flooded with nearby properties located outside of the region of inundation. Whereas information on actual flooding is clearly a better proxy for damages than relying on hazard zones alone, it is still imperfect as a property may be flooded yet escape actual damage due to protective measures (e.g., stilts or flood walls).

Last, information about flood risk is a relatively recent phenomenon. Our third contribution consists in estimating the effect of introducing flood risk information and legally binding preventive measures for houses located in risk-prone areas. The first hydrological hazard maps were introduced in 1997, and coverage was gradually expanded throughout the canton thereafter.

[5] Bakkensen and Barrage (2017) find that around 40% of households substantially underestimate coastal flood risks. Bubeck et al. (2012) report that many individuals have no willingness-to-pay for insurance because they underestimate the (low) probability of flood risk, and that the demand for flood insurance is determined to an important degree by emotional fear. Risk mis-perception can result in spiking insurance take-up after a flood (Gallagher, 2014).

The introduction of a flood risk map provides new information that was previously not available, or only at high transactions costs. Moreover, the risk maps were strictly informational in the beginning but later became a binding component for each property transaction.

Our sample consists of house transactions in the canton of Zurich in the period 2007–2019. Using geographic information software, we match the data with insurance claims, hazard maps and a rich set of additional control variables. First, we analyze the effect of public risk information via hazard maps and examine whether there is a stable price differential as a function of ex–ante flood risk. To reduce the bias due to unobserved variables, we include standard amenities about the building (year of build, surface area, nr. of rooms) and additional information such as the positive amenity of living close to water (i.e., the distance of properties to water such as rivers or lakes), hours of sun per day, distance to the woods and to downtown Zurich and local tax multipliers, all of which turn out to be significant predictors for housing prices in Zurich canton.[6] Next, we run two sets of DiD event study regressions. In the first approach, we define our treatment group as houses located in areas that are subject to flood risk, whereas properties outside of these zones serve as the control group. In the second specification, the treatment group consists of houses located in close proximity to an actual flood damage, whereas properties located further away serve as the control group. To cleanly separate the treated and nontreated properties and thus mitigate a potential violation of the stable unit value treatment assumption (SUTVA), we define a buffer zone of varying radius.

We find that being located in a flood-prone zone has a significant and negative effect on housing prices. In the first specification using hazard zones as the treatment category, the DiD estimates show a significant and negative effect shortly after a flood occurs. However, as only 10% of the actually damaged houses are located in hazard zones, causality cannot be claimed as the separation into treatment and control group is imperfect (in other words, some of the houses in the control group were affected by the treatment as well).

Our preferred approach is the second specification, where we find a negative effect on values of near–miss housing properties relative to houses not located near the flood. This effect is statistically significant and strongest around 1 months after the flood and the effect disappears after a few months. Results are robust to the use of different specifications. Our results imply an

[6] We cannot control for unobserved amenities by using a fixed-effects regressions because most properties were only sold once during our sample period.

informational effect and that home buyers "forget" over time, which has been referred to as an "availability bias" Tversky and Kahneman (1973).

Last, we find that the introduction of hazard maps has a differential effect on house prices depending on the hazard location. Safe houses experience an increasing value, whereas houses at risk are not affected. Our results highlight the value of better flood hazard information and can help guide decision makers when assessing communal benefits gained through flood control and mitigation projects.

The next section provides some more background information and section 3 presents our theoretical model and the econometric specification. Section 4 presents the data and section 5 the results. The last section offers concluding remarks.

## 2 Background

The canton of Zurich, see figure 1, contains 168 political municipalities and is characterized by its capital Zurich and its agglomeration, which occupies most of the canton. The largest body of water is the elongated Lake Zurich, and the major rivers are Limmat, Sihl, Rhine, Glatt, Toess and Thur.[7] We concentrate on the real estate market in the canton of Zurich, which is one of

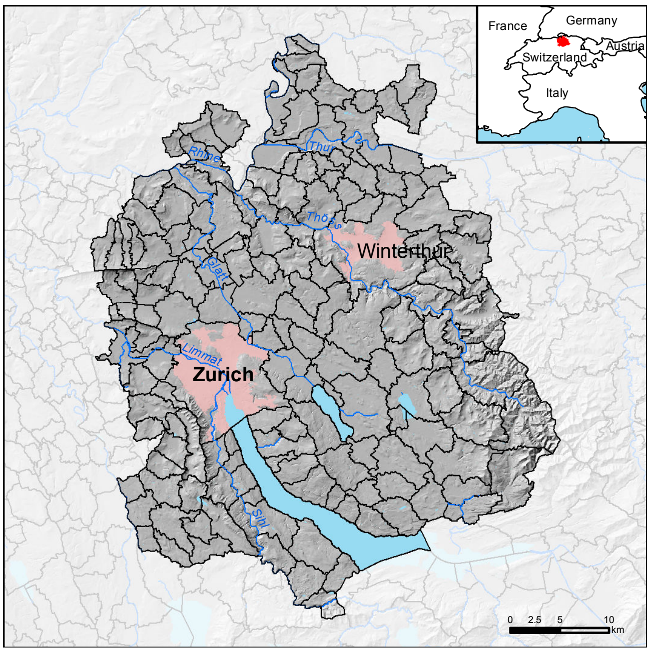



Figure 1: Overview of the Canton of Zurich. Notes: Map of the canton with the main cities Zurich & Winterthur. Map sources: SWISSTOPO (background map, reproduced by permission of SWISSTOPO).

[7] Greifensee and Pfaeffikersee are two other major lakes in the canton and there are various of smaller lakes.

the most important flood risk areas in terms of damages in Switzerland due to its (relatively) large population of close to 1.5 million and the industrial concentration (Tages-Anzeiger, 2012). Between 2007 - 2019, major floods always occurred between April and August.[8]

The real estate market in Switzerland is mostly dominated by locals. Most real estate buyers live in Switzerland as the sale of property to foreigners is restricted and cantonal authorization is needed before gaining title.[9] In Switzerland, buyers and sellers first agree on the price. Afterwards, financing by banks has to be secured and a property transfer has to be made official which means buying offers are held in escrow by a notary where they are signed by both parties. Only then, a property changes ownership, i.e. the date of contract is always prior to the transaction date. On average, the period between price determination and change in ownership is around one to three months.[10]

Very special about Switzerland is its unique social insurance. All buildings in the canton with a value $> 5,000$ CHF have to be insured at the GVZ[11]. Elementary damage by flooding as a result of rainfall (if water penetrates the building on the surface), avalanches, snow pressure and snowfall as well as rock fall and landslide are insured. The insurance is social, which means that everyone pays the same price per building value independent of structural risk.[12] Buildings are socially insured with the structure, the structural cover, the installations and the interior construction. In case of a damage, the GVZ covers the cost of immediate and emergency measures and compensates for the effective demolition, clearing and disposal cost. The deductible is CHF 500 (GVZ, 2017).

In theory, every Swiss homeowner should be informed about possible flood risk at the place of residence. Detailed flood maps in Switzerland (figure 2) indicate the precise location of each property and they are online available to residents (see http://maps.zh.ch). The hazard map classifies an examined area with respect to the magnitude and frequency of potential flood events (Fuchs et al., 2017). The main criteria for classification of the hazard is the flood intensity[13] and

[8] The biggest floods in terms of estimated, caused damages and number of insurance claims are the floods of August 8-9, 2007; June 7, 2015 and May 30, 2018, see section 4.2.

[9] Only EU or EFTA national with a Swiss residence permit residing in Switzerland or individuals with a Swiss C permit can acquire property.

[10] We spoke with different real estate agencies to obtain this approximate time window.

[11] GVZ stands for Gebäudeversicherung Zürich, which is German for building insurance of Zurich.

[12] In 2017, the insurance premium was CHF 0.32 cents (about USD 0.34) for every CHF 1,000 of the insurance value, which is an estimate of the cost to rebuild the house.

[13] The flood intensity with thresholds at 0.5 m or 0.5 $m^2/s$ (yellow and blue), between 0.5 m and 2.0 m or $0.5 m^2/s$ and $2.0 m^2/s$ (yellow and blue), or exceeding 2.0 m or 2.0 $m^2/s$ (red) is used. The probability of occurrence of the underlying flood hazard is used to further distinguish hazard zones for up to 30 year (blue and red), 30-100 year

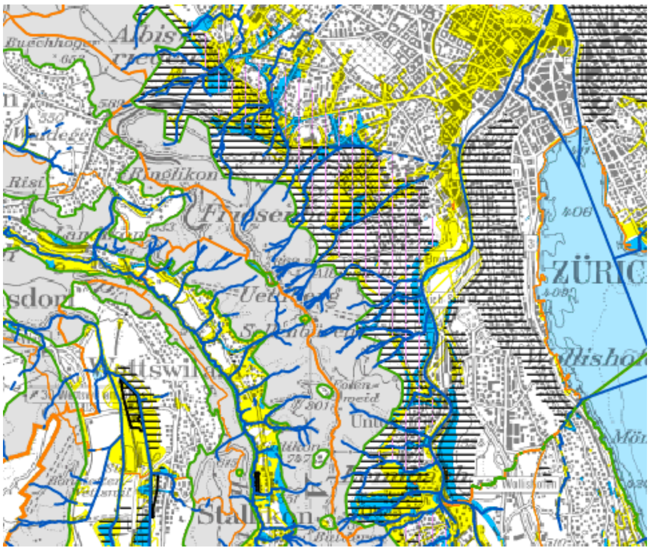


Figure 2: Online available hazard maps. Notes: The figure shows a map section of Zurich's hazard zones. Source: http://maps.zh.ch.

new real estate owners are pointed towards them during the purchasing process. Three main hazard risk classes and related building restrictions exist (Canton of Zurich, 2014a):

Red zones (high hazard): Residents at risk inside and outside of buildings; sudden destruction of a building is possible; any construction of new houses is restricted [14]

Blue zones (medium hazard): Residents at risk outside of buildings; moderate destruction of buildings may be possible. New houses only permitted to be constructed if owner guarantees to implement protection measures. Existing houses have to be adapted in case of modification or extension.

Yellow zones (low hazard): Flood hazard may lead to considerable monetary loss at buildings, but people are rarely at risk; construction of critical buildings, e.g. schools and public buildings is only allowed after a specific sensitivity analysis. Private owners have to declare that they are well aware of the potential risk; protective measures are voluntary.[15]

Hazard maps have not always existed. Only since 1997, flood hazard maps are implemented continuously by the municipalities and by the canton.[16] Once the hazard map has been elaborated

(yellow, blue and red) and 100 to 300 year (yellow and red) return periods.

[16]The guidelines for the consideration of the hydrological hazards in land–use planning activities were approved in

and delivered to the municipality (further referred to as *"mapintro"*), the information of the hazard zones are known and municipalities are required to alert owners in the vulnerable areas to the potential hazards, immediately after the hazard map has been established. But several months up to a few year can pass from the delivery of the maps (i.e. mapintro) to the official implementation ( further referred to as *"compliance"*). Homeowners do have to comply legally with the zone-specific requirements at the official implementation date.

Hazard maps do indeed come into play when evaluating real estate. The "Züricher Kantonalbank", for example, takes into account any additional costs for protective measures and loss of value due to restricted buildability, when evaluation real estate. In the case of existing properties, it is also checked whether the buildings comply with the regulations and permits.

# 3 Theory

We use an illustrative hedonic model adapted to the Zurich real estate market to establish the main hypotheses and to guide our empirical strategy, which we introduce in turn.

## 3.1 Hedonic pricing model

Our hedonic pricing model builds on Bin et al. (2008a). Households are perfectly rational and well informed, both when buying and selling houses.[17] We utilize a hedonic price function (Rosen, 1974), which can be represented as:

$$P = P(s, n(t), r) \tag{1}$$

The price $P$ is a function of structural characteristics $s$, such as the number of rooms or the age of the house, but also location-specific characteristics such as the commuting distance to the next main city using the existing rail and road network, the view, proximity to recreational facilities

1997 (BWW, BRP, and BUWAL, 1997). The municipalities must take into account the requirements of protection against natural hazards in the context of land use planning, revisions of the building and zoning regulations as well as design and district plans. This spatial planning implementation must be integrated into the running processes immediately after the hazard map has been defined, in order to avoid creating new risks in areas at risk (Canton of Zurich Construction Department, 2016).

[17]See Pope (2008) for a critical discussion about this assumption.

and the number of sunlight hours.[18] It also depends on municipality–specific public goods $n(t)$ and the flood risk $r$. The public goods are financed by linear municipality taxes $t$ such that $\frac{\partial n(t)}{\partial t} > 0$. The function $P(\cdot)$ is assumed to be twice continuously differentiable in all arguments and will produce an estimate of the representative household's marginal willingness to pay for an additional unit of an attribute.

Households' utility is strictly concave in all arguments and given by:

$$U(s, n(t), c), \tag{2}$$

with $c$ representing a composite commodity that serves as the numeraire. Consumers are informed about the location-specific flood risk $r$ via the presence of hazard maps, (see figure 2). These are publicly available and have to be acknowledged and singed by the buyer.

We use an expected utility framework in which consumers account for the risk information in their decision making. The observed discount on property prices in an area with high flood risk, relative to safe areas (but all else equal), thus reflects household's willingness to pay to avoid such risk.

The consumer maximizes expected utility over two states of the world. With a probability of $p$, a flood–related damage occurs over a given period of time, whereas with a probability of $1-p$ there is no damage. There exists insurance for the structure of the house and home owners have to pay a deductible. But floods can also cause monetary and non-monetary losses which are not covered by insurance such as personal injury, hassle of being displaced by flood damage, damage to municipality infrastructure, the effort to contact insurance, destruction of items excluded from insurance (such as damages to garden structures or vegetation) and loss of personal items with sentimental value. The parameter $m^L$ represents the expected income in the loss state, i.e., income remaining for consumption of the numeraire, including any insurance settlement net of insurance payments, deductibles and uninsured losses, and $m^{NL}$ represents expected income in the no-loss state, with $m^L < m^{NL}$.

[18]This variable captures the share of the day during which the sun is blocked by nearby mountains and hills. It could therefore also be described as an absence of shade.

The expected utility can thus be written as

$$
\begin{aligned}
E[U] =& p(r)\cdot U^{L}[s,n(t),m^{L}-\lambda\cdot P(s,n(t),r)-t] \\
&+(1-p(r))\cdot U^{NL}[s,n(t),m^{NL}-\lambda\cdot P(s,n(t),r)-t]
\end{aligned}
\tag{3}
$$

where $p(r)$ is the subjective probability of a flood event (based on available hazard maps) and the utility function is state dependent across loss ($L$) and no-loss ($NL$). $\lambda$ is a parameter which converts the sales price to a per-period price.[19] Consumers take the hedonic price schedule $P(\cdot)$ as given and residual income is spent on consumption of the numeraire good. Taking the derivative with respect to housing characteristic $s$, the optimality condition is given by

$$
\frac{\partial P}{\partial s}=\frac{p(r)\frac{\partial U^{L}}{\partial s}+(1-p(r))\frac{\partial U^{NL}}{\partial s}}{\lambda\cdot[p(r)\frac{\partial U^{L}}{\partial c}+(1-p(r))\frac{\partial U^{NL}}{\partial c}]}\,, \tag{4}
$$

which is positive if $s$ is a desirable amenity, and negative otherwise. This states that the marginal "implicit hedonic price" for amenity $s$ is equal to the ratio of the expected amenity value and the expected marginal utility of income.

The price for housing is also influenced by local tax rates. The optimality condition for $t$ is

$$
\frac{\partial P}{\partial t}=\frac{p(r)[\frac{\partial U^{L}}{\partial n}\frac{\partial n(t)}{\partial t}-\frac{\partial U^{L}}{\partial c}]+(1-p(r))[\frac{\partial U^{NL}}{\partial n}\frac{\partial n(t)}{\partial t}-\frac{\partial U^{NL}}{\partial c}]}{\lambda\cdot[p(r)\frac{\partial U^{L}}{\partial c}+(1-p(r))\frac{\partial U^{NL}}{\partial c}]} \tag{5}
$$

where we have applied $\frac{\partial U^{L,NL}}{\partial c}\frac{\partial P}{\partial n(t)}\frac{\partial n(t)}{\partial t}=\frac{\partial U^{L,NL}}{\partial c}\frac{\partial P}{\partial t}$. If the marginal utility of income exceeds the marginal utility of a tax increase financing the municipality–public good, i.e., $\frac{\partial U^{L}}{\partial c}>\frac{\partial U^{L}}{\partial n}\frac{\partial n(t)}{\partial t}$, a tax increase has a negative effect on housing prices, and vice versa.

Hypothesis 1 (H1) is motivated by the marginal effect of (exogenous) risk on housing prices, which is given by

$$
\frac{\partial P}{\partial r}=\frac{\frac{\partial p(r)}{\partial r}(U^{L}-U^{NL})}{\lambda\cdot[p(r)\frac{\partial U^{L}}{\partial m}+(1-p(r))\frac{\partial U^{NL}}{\partial m}]}<0. \tag{6}
$$

The marginal price for risk is equal to the difference in utility by the two states, weighted by the marginal probability of risk $\frac{\partial p(r)}{\partial r}(U^{L}-U^{NL})$ and divided by the expected marginal utility of income. As $m^{L}<m^{NL}$ such that $U^{L}>U^{NL}$, an increase in flood risk will have a negative price

[19]This period could be any number of years. Since the same period applies for both states of the world, neither the length of the period nor the discount factor are relevant.

effect, which constitutes H1. A finding of no price differential between risky and safe zones could be due to a small difference between $U^L$ and $U^{NL}$, which is the case if the uninsurable costs are small, or if consumers underestimating flood risk at the time when they purchase a house.

In the absence of shocks, buyers can potentially become insensitive to environmental risk factors, especially in the presence of socialized insurance that is insensitive to the actual risk. Furthermore, without any risk information, e.g. in form of hazard maps, homeowners do not have any prior knowledge about their potential flood risk. We know the specific date when home owners learn their respective flood risk once the hazard maps are implemented (mapintro) and the specific date, once compliance with the maps is binding. There are two possibilities, in which direction a price adjustment can take place once information is available. If home owners learn about a risk increase, we expect a negative effect on housing value, see equation (6). However, if the safe location of a house is officially confirmed, we expect a positive effect. This establishes our second hypothesis (H2). We also investigate whether there is a difference between the pure information about the hazard zone (mapintro) and the associated future protective measures that must be taken and the binding, legal obligation which comes once the hazard map is established, that is only binding later (compliance).

The occurrence of a flood may lead to a revision of expectations based on hazard maps, as new information is available. If this information was available before, but simply forgotten, then this is called an availability bias. Since an availability bias has been shown in previous studies Gallagher (2014), our third hypothesis (H3) states that the price differential should become larger in the aftermath of a flood.

Finally, note that if the uninsurable costs are simply too small to matter empirically, then we should see no effect after a flood or the introduction of hazard maps.

## 3.2 Empirical strategy

We introduce our empirical framework and identification strategy to investigate our hypotheses. In a first step, we estimate a baseline hedonic price regression to learn if flood risk has a negative price effect (H1). The equation takes the following form:

$$ln(P_{ijd}) = \beta_0 + \beta_1 ln(S_i) + \beta_2 ln(T_{jd}) + \beta_3 hazard_i + \zeta_j + \theta_\mathrm{d} + \mu_\mathrm{d} + \eta_\mathrm{d} + \epsilon_{ijd} \tag{7}$$

The dependent variable is the (log) price per square meter of the sold property (footprint) $i$ in zip code area $j$ on date $d$.[20] The independent variables are the following. The dummy variable $hazard_i$ indicates whether the property is located in a flood hazard zone (low or medium). The vector $S_i^k$ includes different structural characteristics such as the number of rooms, the actual surface area of the house (allowing for the possibility that the price increases non-linearly), the defined building zone, the house's age and the calculated location–specific property attributes, see below. We also include a dummy to indicate a damage based on insurance claims information. We furthermore control for municipality taxes $T_{jd}$. To control for regional unobservable characteristics that may determine housing prices, we include a set of zip code dummies $\zeta_j$. We further include weekday fixed effects $\theta_\mathrm{d}$ and month fixed effects $\mu_\mathrm{d}$ to control for weekday and month - specific seasonality. The term $\theta_\mathrm{d}$ contains year fixed effects.

The standard errors are clustered on the municipality level, which can include several zip codes.[21]

Our second hypothesis addresses the introduction of hazard maps (mapintro and compliance) and the effect on house prices. We estimate the following regression:

$$\begin{aligned} ln(P_{ijd}) = {} & \beta_0 + \beta_1 ln(S_i) + \beta_2 ln(T_{jd}) + \beta_3 hazard_i + \beta_4 \cdot date_{dj} + \\ & \alpha \cdot (hazard_i \times date_{dj}) + \zeta_j + \theta_\mathrm{d} + \mu_\mathrm{d} + \eta_\mathrm{d} + \epsilon_{ijd} \end{aligned} \tag{8}$$

We run two versions of equation 8. In the first version, the variable $date_{dj}$ specifies the data when the hazard maps were delivered to the municipalities and the hazard zone information was communicated to the homeowner (mapintro). In the second version $date_{dj}$ is equal to the compliance date since guidelines for the hazard maps became binding. We interact this date with the low, medium and no hazard zone to learn if the effect differs between hazard zones.

To identify the information effect (H3), we obtain insurance claims and match them with the transaction prices (for details, see section 4) in order to use two different approaches to separate treated from control units. In the first estimation, we follow the previous literature and define the

[20]Our data include all property transactions during our time frame. We do not have a panel, as only few properties were sold more than once during our sample period, and any number of sales (including zero) can occur on a particular $d$. To control for unobserved heterogeneity, we include regional and time dummies.

[21]All relevant local decisions are taken on the municipality level. We use zip code dummies to capture neighborhood effects and thus to allow for more and less desirable regions within a municipality. The zip code level is the lowest level of regional differentiation in Switzerland, as there is no equivalent to the "census tract" used in the USA.

treatment group as those properties that are located in flood-prone areas defined by the hazard maps, whereas the control group consists of properties located outside of flood hazard zones. In our second approach, we compare the prices for Near–miss properties (treatment group) and prices of all other properties further away, which are unaffected by flooding (control group) after the major floods. This methodology is similar to Beltrán et al. (2018a), but we use actual damages to identify the treatment rather than the zip code specific inundated locations as in that study. In addition, to separate treatment and control group more precisely, we include a spacial buffer, see section 4.2 for more details. If informational updating takes place as home owners might underestimate flood risk, being a Near–miss after the occurrence of a flood should lead owners to update their subjective probability of future flooding.

We use the following DiD event study design to estimate the effect of flood events on prices:

$$ln(P_{ijd}) = \beta_0 + \beta_1 ln(S_i) + \beta_2 ln(T_{jd}) + \beta_3 treat_i + \beta_4 \cdot flood_d^t + \\ \alpha \cdot (treat_i \times flood_d^t) + \eta_{\mathrm{d}} \times \zeta_j + \theta_{\mathrm{d}} + \mu_{\mathrm{d}} + \epsilon_{ijd}. \quad (9)$$

Here, the dummy $flood_t^d$ takes the value of one if date $d$ is within $t$ months of a flood event (see below), and zero otherwise. The variable $treat_i$ is either the Near–miss group or the hazard group. The coefficient $\alpha$ on the DiD-term $(treat_i \times flood_t^d)$ is the average treatment effect on the treated (ATET).[22]

To elaborate on the time profile of the flood effects, we pool all flood events and construct a series of $t$ flood dummies $flood_d^t$, which take the value of 1 if the sale date $d$ is within $t$ months after a flood event. Figure 3 provides an example of the construction of these dummies for the years 2007 to 2009. Each flood dummy is specified to measure the effect within $t$ months before or after the flood event. For example, $flood_d^2 = 1$ on all dates for sale dates that occur 31-60 days after the flood event, whereas $flood_d^3 = 1$ for sale dates that occur 61–90 days after the

[22] Following Wooldridge (2010), we can define $\bar{y}_{h1}$ as the sample average of the treatment (=hazard /NM) group before a flood (period 1) and $\bar{y}_{h2}$ after the flood. $\bar{y}_{c1}$ is the sample average of the control group in state period and $\bar{y}_{c2}$ after the flood. The ATET is given by:

$$\alpha = (\bar{y}_{h2}|_{X_{h2}} - \bar{y}_{h1}|_{X_{h1}}) - (\bar{y}_{c2}|_{X_{c2}} - \bar{y}_{c1}|_{X_{c1}})$$

Hence, we compare the time change in means for treatment and control group. This framework allows us to isolate the effect from the flood from other contemporaneous characteristics (e.g. local housing market changes, macroeconomic shocks). In order to reduce the bias potentially introduced by observable differences across groups, we condition on observable covariates $X = (S, T)$ as discussed in the text.

flood event. To limit the effect window to a finite number of leads and lags, we are binning the endpoints of the window.[23]

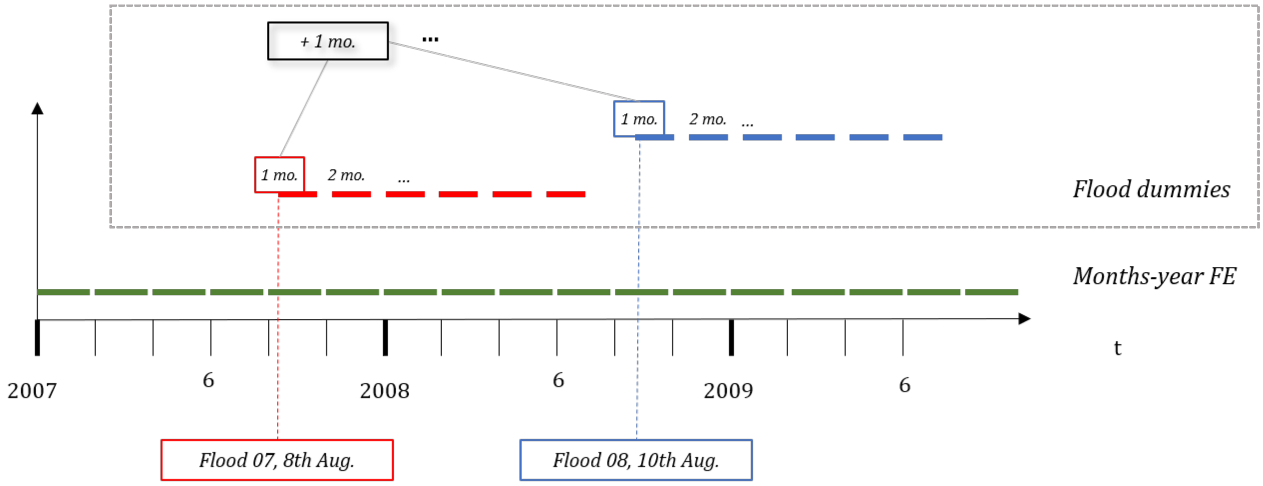



Figure 3: Flood dummies and identification of flood effect. Notes: The dummies are used in equation (9). The time window 2007 - 2008 is used as an example and we illustrate the the use of the flood dummies and month–year FE. Month–year FE will be used as a robustness check.

To obtain unbiased estimates, we need the usual assumptions of common or parallel trends, unconfounded assignment to treatment and stable unit treatment value assumption (SUTVA).

Adding the additional covariates in the regression, we assume that the control group serves as an appropriate counterfactual for calibrating flood risk premiums in property prices over time. This is true if any confounding omitted variables affect both treatment and control groups similarly. Figure 5 and 6a show the raw data with approximately similar trends over time, but it is important to note that this period includes several floods and is therefore not "pre-treatment".[24] This can further be tested indirectly by carrying out placebo tests using previous periods which we do by showing the event study coefficients "before" the actual floods.

An unbiased estimation of the ATET requires that the floods are not systematically related to unobservable price determinants that end up in the error term $\epsilon_{it}$. We follow Gallagher (2014) and argue that, conditional on a municipality's geography and time trends, whether or not a municipality is flooded in a particular year is random and households do not anticipate the specific timing of the event. In this sense, the assignment to the treatment is unconfounded.

For SUTVA to hold, it must be the case that the treatment does not affect the control units.

[23]The implementation of an event study design (implicitly) assumes that there is no effect after e.g. 8 months, treating observations outside this range as control group like the observations at the flood event. This strong assumption could be avoided by so-called binning of the endpoints, see Schmidheiny and Siegloch (2019).

[24]This applies even to the days before the first flood event in the sample, as there were previous floods that occurred previous to our sample period.

Taken at face value, this is unlikely to hold within the Zurich real estate market. If some properties become less desirable due to a change in the risk assessment, it is of course possible that safe locations experience an increase in demand. This would lead to a negative correlation of the flood-related effect on the treatment and the control group, and thus to an over–estimate of the effect. Although we cannot rule out this bias, we argue that the share of properties at risk relative to safe locations is sufficiently small such as to dilute the potentially price-increasing effect of a flood on the control group. For our Near–miss specification, we furthermore include a spacial buffer to differentiate the control and treatment group more precisely, which improves our argument for SUTVA to hold, see section 4.2.

# 4 Data

In this section, we describe our main data: Insurance claims, hazard maps, property prices and location–specific property attributes.

## 4.1 House prices

We use GIS data on house prices for 2007–2019 provided by the Canton of Zurich Statistical Office (2019b). The data contains information about the number of rooms, sales year, municipality, age of the building, the building zone and the transaction certification date on a daily base. Defined building zones are single family houses zone, business, mixed zone, remaining municipality district, wood, farming zone, reserve zone, public zone, no-building zone, multiple family houses zone. The location is given in the form of a point (x/y coordinates). We convert the nominal prices to real prices using the CPI provided by the Federal Statistical Office (2019). We correct for outliers by excluding the bottom and top 5 % of transactions.

## 4.2 Insurance data and flood events

The GVZ insurance company has a monopoly on the insurance of losses to the structure of buildings in the canton of Zurich. Due to the mandatory nature of building insurance, the entire housing stock of Zurich canton is insured by GVZ. We obtained confidential, geo-referenced damage data from the GVZ that includes *all* claims made between 2006–2019, which are related to flooding (GVZ, 2019). The data is anonymous in the sense that no names or addresses are revealed, only the geographical coordinates in the form of a point.[25] To be precise, the data contain the location, the date and a variable specifying the severity of the damage, i.e. whether the claim is a loss above the median. The average claim between 2006 – 2019 values 10,586.40 CHF, see table A.3 for more details.

To obtain information about the economic severity of flood events between 2007âĂŞ2019, we rely on the Swiss flood and landslide damage database managed by the Swiss Federal Institute for Fores, Snow and Landscape Research WSL (for more information, see Hilker et al. (2009)[26]

Table 1 lists the main flood events during out sample period with approximated economic damages, the number of insurance claims and the number of paid claims.

Table 1: Main floods in the canton of Zurich 2007 - 2019

| **Flood Date** | **Diff. in weeks** | **Diff. in months** | **Damage [Mio. CHF]** | **WSL** | **No. of all GVZ Claims** | **No. of paid GVZ Claims** |
|---|---|---|---|---|---|---|
| 21.06.2007 | | | | 6.4 | 690 | 264 |
| 08.08.2007 | 6.9 | 1.7 | | 10.1 | 1141 | 210 |
| 10.06.2008 | 43.9 | 11.0 | | 1.8 | 512 | 297 |
| 10.07.2010 | 108.6 | 27.1 | | 0.1 | 324 | 106 |
| 27.07.2011 | 54.6 | 13.6 | | 1.9 | 225 | 168 |
| 01.07.2012 | 48.6 | 12.1 | | 0.6 | 446 | 119 |
| 02.05.2013 | 43.6 | 10.9 | | 5.7 | 726 | 430 |
| 12.07.2014 | 62.3 | 15.6 | | 1.1 | 314 | 137 |
| 07.06.2015 | 47.1 | 11.8 | | 8.4 | 599 | 386 |
| 30.05.2018 | 155.4 | 38.9 | | 26.6 | 1378 | 1167 |

Notes: The table presents the main floods in the canton of Zurichthe difference between the floods (weeks and months) and the number of approximated damages from Hilker et al. (2009) combined with damage data from GVZ (2019).

We see that the biggest floods are by far the 8th of August flood 2007 and the 30th May Flood 2018 with over > 1100 claims. All main floods occured between May and August. We use the 10 biggest floods from table 1 to construct our $flood_d^t$ dummy variables as described above (see figure 3). This means in turn that there is an overlap for the effect of the two flood 2007 which enter the flood dummies as we are carrying out a pooled event study. The shortest interval between two floods (except for 2007), which do not directly follow each other, is around 11 months. Therefore,

[25]To protect the identity and valuation of individual properties, detailed data on monetary losses are confidential and not available to us, only a dummy indicating whether a claim was filed and paid out and if the claim was above the median.

[26]Total damage cost = total property damages + total damage to infrastructure + total damage to forest + total damage to agriculture. The damages provided by Hilker et al. (2009) are estimate aggregate damages based on newspaper reports and the amounts of damage are as such incomplete.

we only consider the time window of -2 – +9 months in our pooled event study.

To identify damaged houses, Near–misses as well as Non–Near–misses, we match the property transactions with the dates and locations of the flood loss claims. Each house has a unique GVZ insurance number which is provided by Canton of Zurich Statistical Office (2019b) as well as by the GVZ (2019). This allows us to identify actual damaged houses very precisely. In a next step, we compute the Euclidean distance between each house and the damaged houses using the coordinates. Next, we need to separate the non–damaged properties into those that narrowly missed a flood damage (Near–misses), and those that were located at a safe distance (Non–Near–misses). There is a trade–off between sample size and accuracy when defining the radius of the Near–miss specification. As the radius is increased, the number of treated observations increases too, but we add an increasing number of houses that were not particularly close to the damage and therefore did not receive the "treatment". This dilutes the treatment effect as more unaffected properties are lumped together with the treated ones, and is similar in spirit to a classical measurement error. On the other hand, choosing a radius that is too narrow has two different costs: First, the number of observations decreases quickly. For example setting the radius at 100m leads to 462 observations, in which only 20 would be in the treatment group, for example after two–three months. Second, and perhaps more importantly, some home buyers may consider a distance of, say, 250 m from a damage a "near-miss" event. By classifying this as a control unit, we violate SUTVA (the control group is affected by the treatment). To gain more intuition about these effects, we start by specifying a distance of 50- <400 m as a Near–miss (i.e., no closer than 50 m but no further than 400 m from a recorded damage), whereas the control properties are defined to be > 700m away and not damaged. This means we include a buffer of a bandwidth of 300m. Precisely, we define near-miss as 50–500 m away, but the control houses are at least more than 700 m away from the damage. The houses located between >400 and <700 are excluded from the analysis, as it is not clear whether they belong to the treatment or the control group. This reduces the number of observations, but likely improves our argument for SUTVA to hold. Figure 5 confirms that the average yearly house and land prices differentiated by Near–misses (400m) and non–near-misses follow roughly a similar trend.

Figure 4: House price development by Near–miss 400m and non-Near–misses

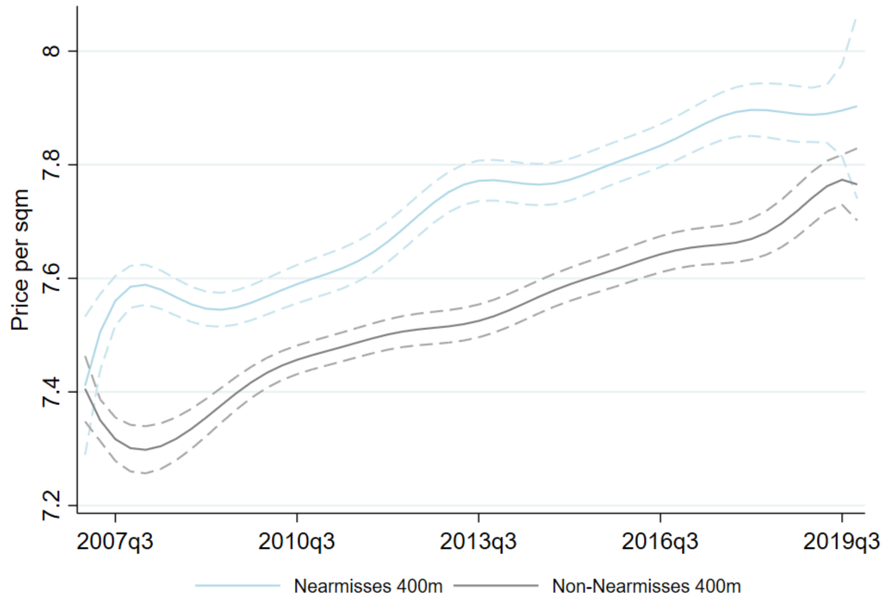



Figure 5: Average house price development from 2007 - 2019. The solid lines are fitted using kernel-weighted local polynomial regression, using a Gaussian kernel, a polynomial of degree three, and a bandwidth of four quarters.

## 4.3 Hazard maps

We obtain the hazard maps from the Canton of Zurich Statistical Office (2019a). Their geographic scale varies between 1:2,000 and 1:10,000. Using consistent GIS data, we attribute the hazard zones to houses by georeferenced overlay (Fuchs et al., 2015; Röthlisberger et al., 2017). The houses are represented spatially by a point while the hazard zones are represented by polygons. Thus, the attribution of the hazard category to the houses can be done in two ways. The first is a direct attribution by the location of the point. This could underestimate the number of exposed buildings in the neighborhood of the hazard zones, especially for large buildings. Thus we attribute the hazard zone to an auxiliary data set of the building footprints (Röthlisberger et al., 2018), and consequently use these categorized building footprints to attribute the hazard zone to the house represented by a point. The building footprint polygon thus act as a bridge for the information attribution (Zischg et al., 2013). In the latter approach, the situation in which a house is located with one edge in a flood zone but the centroid is located outside, is considered. We use the latter approach in the main analysis.

In our analysis, we construct two versions of hazard dummies. First, we compute a categorical variable, which differentiates between medium, low and no hazard zones. Since the treatment group sample size would be to small to estimate a DiD, we further combine the blue and yellow hazard zones and constructs an additional hazard dummy that is equal to one if a property is located in a hazard zone (of any color), and zero otherwise.[27]

Several months up to a few year can pass from the delivery of the maps (i.e. the “mapintro”) to the official implementation (“compliance”). We attributed both dates to our data set. The dates of elaboration and implementation were collected from the cantonal authorities in Switzerland (Bruchez, 2017). We construct the variables $mapintro$, which is a dummy equal to one if the date when the hazard map has been elaborated and delivered to the municipality; and $compliance$ is a dummy equal to 1 if the mandatory building restriction date is binding. The dates are available on a yearly basis.

Figure 6a shows no clear indication whether the price level of the risky zones is significantly below the no-hazard zones. Figure 6b illustrates the average number of houses sold per months for the period 2007 – 2019 divided by hazard and non-hazard zone. We do not see graphical evidence, which might suggest that houses sold after floods are so-called “fire-sales”.

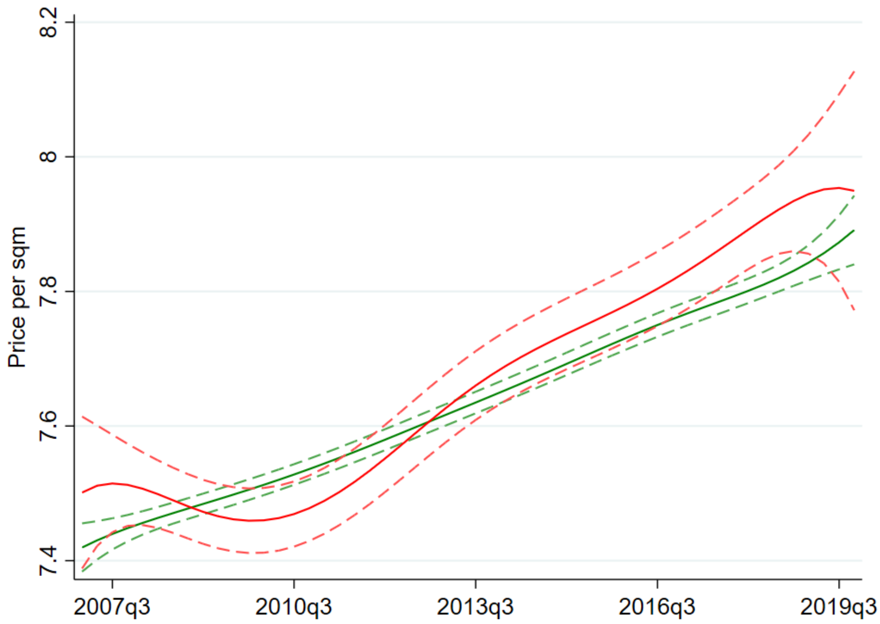
### 4.4 Location-specific property attributes

Figure 5 and 6a show the raw data without controlling for potential confounding factors. The difference may capture the flood risk, but also other characteristics that are desirable characteristics by themselves but likely correlated with the flood risk. Based on our geo–referenced data we can calculate a rich set of control variables. Specifically, we control for location–specific amenities such as the distance to water courses, the distance to recreational forests, the visible area, the maximum distance of visibility towards the horizon, the distance to the center of Zurich, and the average of yearly solar radiation.

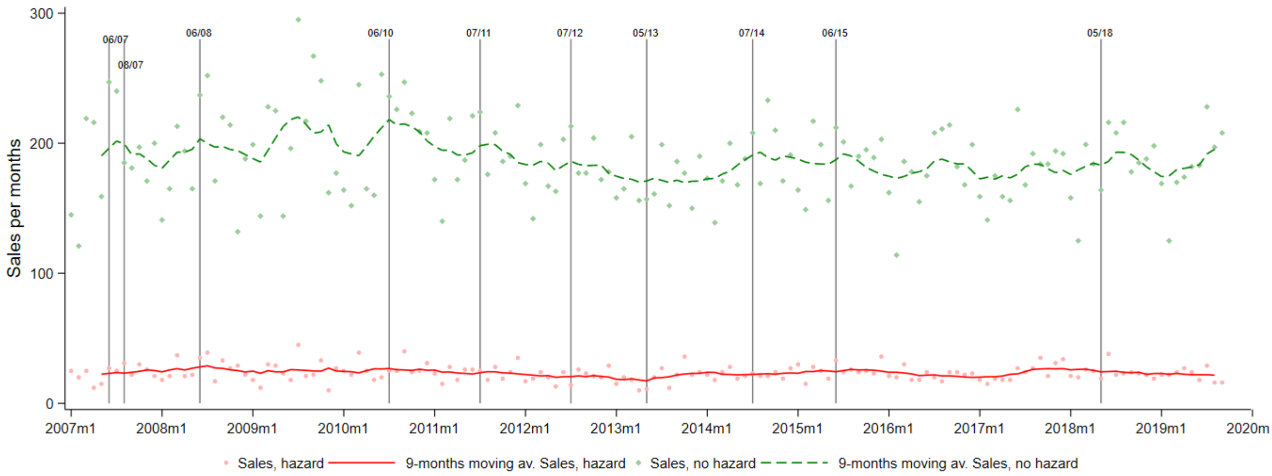
The positive amenity of living near by the water can be highly correlated with risk location (see Bin et al., 2008b, for a discussion).[28] To obtain the measure distance to water, we compute the Euclidean distance of each location to the next water polygon. Similarly, we capture distance

[27]Only one transaction point is partially located in the red zone and thus is dropped.

[28]Daniel et al. (2009) argue furthermore that "previous studies often fail to adequately take into account the positive effect of a location close to the water and that the literature would benefit from alternative methodologies that better incorporate this confounding variable." One simple variable capturing the location of a risky floodplain may underestimate the value of the risk of river flooding, as the positive and negative amenities of living close to the water are not separately identified, and can partly cancel out in house prices”.




(a) House price development




(b) Number of houses sold

Figure 6: House price development by hazard zones. Notes: Figure 6a shows average house price development from 2007 - 2019. Average house price development from 2007 - 2019. The green line are the non-risky sqm prices and the red line are sqm house prices in hazard zones. The solid lines are fitted using kernel-weighted local polynomial regression, using a Gaussian kernel, a polynomial of degree two, and a bandwidth of seven quarters. Figure 6b shows monthly average housing sales from 2007 - 2019 and the main flood events. The solid lines are nine months moving averages and dots are observations.

to recreational forests to capture the access to recreational areas.[29]

To control for the view, we compute the area that is visible from each location of the sold houses (based on the centroid).[30] From the mapped visible area for each location, we then extracted the maximum distance to the horizon which is used as a control.[31]

We calculate the distance to the center of Zurich (central train station) by means of the shortest path along the main road network, which we extract from the national terrain model of the Federal Office for Topography (SWISSTOPO, 2018c). Moreover, we compute the solar radiation throughout the year on the basis of the digital terrain model with a grid size of 25m (SWISSTOPO, 2018a) following the method and parameter sets suggested by (Zgraggen, 2001). More precisely speaking, this is the potential solar radiation due to (absence of) shading by nearby mountains and hills, but it does not include meteorological phenomena such as clouds or fog. The micro–topography of the structure itself and shadowing by nearby houses have not been considered as we do not have data about the exact shape and height of the buildings, only about the footprint.

Because the fiscal conditions are an important determinant of locational choice and thus of housing prices (see, e.g., Schmidheiny, 2006), we match our data with municipality–specific personal tax shifters provided by the Canton of Zurich Statistical Office (2020). These linear tax shifters are determined locally and define the percentage of the (progressive) cantonal tax that has to be paid to the municipality. Property prices may also be affected by neighborhood effects that capture, for example, the presence of local public goods or the "quality" of neighbors (see, e.g., Ioannides and Zabel, 2008). To control for these unobserved characteristics, we include zip–code dummies in our regressions, as discussed in section 3.2. Detailed summary statistics of of the used variables can be found in the Appendix A.2, see table A.2.

# 5 Results

We start by presenting the results from the "difference" regressions, followed by the DiD regressions.

[29]This data set was extracted from the national topographic map at the scale of 1 : 25000 of (SWISSTOPO, 2018b).

[30]The neighboring houses are not considered in these calculations. The visibility was calculated on the basis of the digital terrain model.

[31]Maximum distance to the horizon depends on the observers height. For an observer on the ground with eye level at e.g. 1.70 m, the horizon is at a distance of 4.7 km. For an observer standing on a hill with 30 m in height, the horizon is at a distance of 19.6 km.

## 5.1 Differences in risk levels and hazard information

Table 2 presents the results for equation (7). Being located in a flood hazard zone has a significant negative effect on housing prices (column 1), which confirms hypothesis H1. When separating the effect of being in a low vs. medium hazard group (column 2), we find a significant effect for the former, but not the latter, which is presumably due to the fact that the low-hazard category contains many more properties than the medium–hazard category (see table A.2). The price discount implies that the mandatory building insurance is in fact not complete, and that the risk related to the uninsurable costs of flooding is reflected in house prices.

A past flood damage (i.e., the dummy indicating that an insurance claim exists before the house was sold) has a significant and positive effect on housing prices. This may be due to the fact that by the time the house is sold, the damage has been repaired and better equipped as before, such that the new buyer does suffer any costs from the damage. In fact, a house may be fully or partially renovated in the wake of a flood damage, which increases the value. This could offset the price discount of recently damaged houses.

The effects of the structural and location–specific characteristics are mostly as expected. The price of a house increases, ceteris paribus, if it is newer, has more bedrooms, has a wider view, is exposed to more hours of sunshine and is located in a more urban area (and hence further away from the forest). The price per $m^2$ decreases with the size of the house which is consistent with the results by Lin and Evans (2000). The maximum distance of visibility from the center pixel of the house (excluding the neighboring houses, in meters) has a negative but insignificant effect on housing prices.

In Zurich - the largest agglomeration in Switzerland - almost 774,000 people commute on an average working day. The majority of them (535,284) are Zurich residents themselves who travel to work in their own places of residence. In addition, there are over 166,000 people who commute to work in Switzerland's largest city (Wiget, 2017). It is not surprising that commuting distance to Zurich negatively affect housing prices.

Municipality–specific tax rates have a significant positive effect. The positive tax effect can be explained, if house buyers associate an increase in taxes with a corresponding increase in public expenditure. If the marginal utility of public goods is higher than marginal utility of income, taxes have a positive effect, see equation 5. This is consistent with Brülhart et al. (2017) who find that

Table 2: Baseline results

| | *Dependent v.:* Ln price sqm, real | |
|---|---|---|
| | (1) Hazard, 2 cat. | (2) Hazard, 3 cat. |
| Hazard | −0.013** | |
| | (0.006) | |
| Low hazard | | −0.016** |
| | | (0.008) |
| Med. hazard | | 0.009 |
| | | (0.015) |
| damage | 0.019** | 0.019** |
| | (0.008) | (0.008) |
| Ln (rooms) | 0.348*** | 0.347*** |
| | (0.010) | (0.010) |
| Ln (size) | −0.586*** | −0.586*** |
| | (0.006) | (0.006) |
| Ln (age) | −0.155*** | −0.155*** |
| | (0.008) | (0.008) |
| Ln (distZH) | −0.246*** | −0.246*** |
| | (0.086) | (0.086) |
| Ln (distforest) | 0.006 | 0.006 |
| | (0.005) | (0.005) |
| Ln (radiation) | 0.625*** | 0.624*** |
| | (0.094) | (0.094) |
| Ln (tax) | 0.078** | 0.078** |
| | (0.038) | (0.038) |
| Ln (vismaxdist) | −0.002 | −0.002 |
| | (0.003) | (0.003) |
| *Constant* | 10.213*** | 10.213*** |
| | (0.995) | (0.996) |
| Weekday FE | ✓ | ✓ |
| Month FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Zip code FE | ✓ | ✓ |
| Observations | 21,765 | 21,765 |

Notes: Results from estimating (7). The dependent is the log price per square meter. Standard errors (in parentheses) are clustered at the municipality level. We restrict the sample to sales for which a hazard map was available at the transaction time. No hazard is in both specifications the ref. category. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

higher-income households attach relatively more weight to publicly provided goods such that they benefit more from an expenditure increase which is to some extent capitalized into (renting) housing prices.

Hazard maps have not always been available. Table 3 shows how property prices were affected by the introduction of flood hazard maps (*mapintro*) and their legal obligations (*Compliance*). The introduction of hazard maps significantly increases the price of buildings outside the hazard zone by almost 7%. Similarly, the binding legal guidelines associated with the hazard maps are positive for non-risky houses. This is intuitive: Being officially cleared of flood risk is equivalent to a decrease in risk, which increases the value of the property. This is partially in line with hypothesis 2.

In contrast, the effects of the introduction of hazard maps and the hazard map compliance on low and medium hazard zones are negative but insignificant. We can think of two explanations for this result. First, it is possible that the expected flood risk is most similar to the category "low or medium hazard", such that the assignment into this category in a new hazard map does not lead to an updating of the risk assessment for these properties. In other words, although the flood risk is priced into property prices (see table 2), the prices remain stable if the perceived risk remains constant. Another explanation, which may hold instead or in addition to the above argument, is based to the rules associated with the hazard assignment. Being assigned to low flood protection measures in low hazard zones are voluntary, such that assignment to this category does not necessarily lead to an increase in costs. Although owning a house in medium flood risk requires homeowners to implement flood protection measures, which are quite costly for an existing structure, they might increase the value of the house at the same time such that the net effect is zero. Overall, we conclude that the cantonal introduction of hazard maps is not sufficiently capitalized into housing prices.

Table 3: Introduction of hazard maps

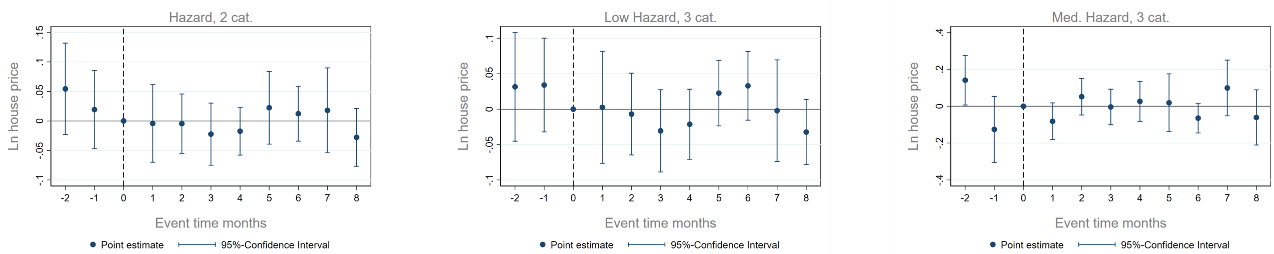
| | *Dependent v.:* Ln price sqm, real | |
|---|---|---|
| | (1) Mapintro | (2) Compl. |
| Low hazard | 0.004 | −0.017* |
| | (0.042) | (0.010) |
| Med. hazard | 0.080 | 0.016 |
| | (0.073) | (0.020) |
| Mapintro | 0.066*** | |
| | (0.022) | |
| Low h. × Mapintro | −0.018 | |
| | (0.043) | |
| Med. h. × Mapintro | −0.071 | |
| | (0.074) | |
| Compliance | | 0.021*** |
| | | (0.007) |
| Low h. × Compl. | | 0.007 |
| | | (0.014) |
| Med. h. × Compl. | | −0.011 |
| | | (0.031) |
| *Constant* | 10.547*** | 10.541*** |
| | (0.515) | (0.514) |
| Controls | ✓ | ✓ |
| Weekday FE | ✓ | ✓ |
| Month FE | ✓ | ✓ |
| Year FE | ✓ | ✓ |
| Zip code FE | ✓ | ✓ |
| Observations | 22,336 | 22,336 |

*Note:* The table presents results from estimation equation (9), standard errors in parentheses are clustered at the municipality level. Dependent variable is the Ln price / sqm. Mapintro is the data once the hazard maps were introduced but legal obligations were not binding and compliance is the data when obligations were binding. We do not control for distance for water due to collinarity with the hazard zone variable. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

## 5.2 Difference-in-difference regressions

The estimates in table 2 – 3 may suffer from omitted variable bias if unobserved house price determinants are correlated with the flood zone assignment. The trust we place in this estimator depends on the extent to which we can control for the most important determinants of house prices. To relax the assumption of being able to control for all relevant house price determinants, we carry out two sets of DiD regressions.

Figure 7 visualizes the DiD event study results for estimating equation (9) following the previous literature using hazard zone location as the treatment group. The time window -30 - 0 days before the flood serves as the reference category in figure 7. Table A.4 in Appendix A.4 provides the results DiD event study results. Although the pattern of the coefficients suggests that prices




(a) House prices, hazard vs. non-hazard zone, 2 cat.

(b) House prices, Low hazard vs. non-hazard zone, 3 cat.

(c) House prices, Med. hazard vs. non-hazard zone, 3 cat.

Figure 7: Flood Effects 2007 - 2019, hazard zones. Notes: The figures plot event time coefficients from estimation of equation 9 with hazard zones (one, low, medium) as the treatment group on the 2007-2019 house price panel. Each point illustrates the average effect after e.g. 1–2 months (=2 on the x-axis). The bars show the 95 percent confidence interval. The vertical axis measures ln house prices. The reference category is the time window of -1 - 0 months before the flood. Endpoints are binned.

decrease slightly after floods, the effects are not significant and we conclude that there is no effect. A variety of studies are based on the information contained in the flood hazard maps, which is an ex-ante measure of risk. Price discounts in the aftermath of floods have been previously identified, but according to Atreya and Ferreira (2015) this was largely driven by an inundation effect or a damage effect rather than an information effect. Using our insurance data that contains information about actual damages, we address this issue in our first DiD estimation. Controlling for actually damaged properties, we can isolate the information effect from damages and we do find no effect.

Only a small share of the properties in a hazard zone are usually affected by a flood, and damages also occur in zones designated as having no flood hazard.[32] In this sense, the hazard information from the official maps is an imprecise estimate of actual damages. The problem of imprecise measurement using hazard maps can further be interpreted as a measurement error: Hazard maps over–estimate the flood risk for non-affected properties in the hazard zone and under–estimated it for affected properties in the zero-hazard zone. The latter is also a clear violation of SUTVA, as the treatment also affects the control group. Addressing this issue, we can cleanly identify treated and non–treated units by focusing on Near-misses in our second DiD specification.

Figure 8 plots the event study point estimates of the DiD coefficients for house prices with -30 - 0 days as the reference category. The DiD effect on house prices in the months before a flood is statistically not different from 0, which serves as a kind of placebo test. There is a significant decrease in house prices between zero and one month after the flood time stamp. Afterwards, the effect declines and becomes statistically insignificant. Recall that our data contain the date when

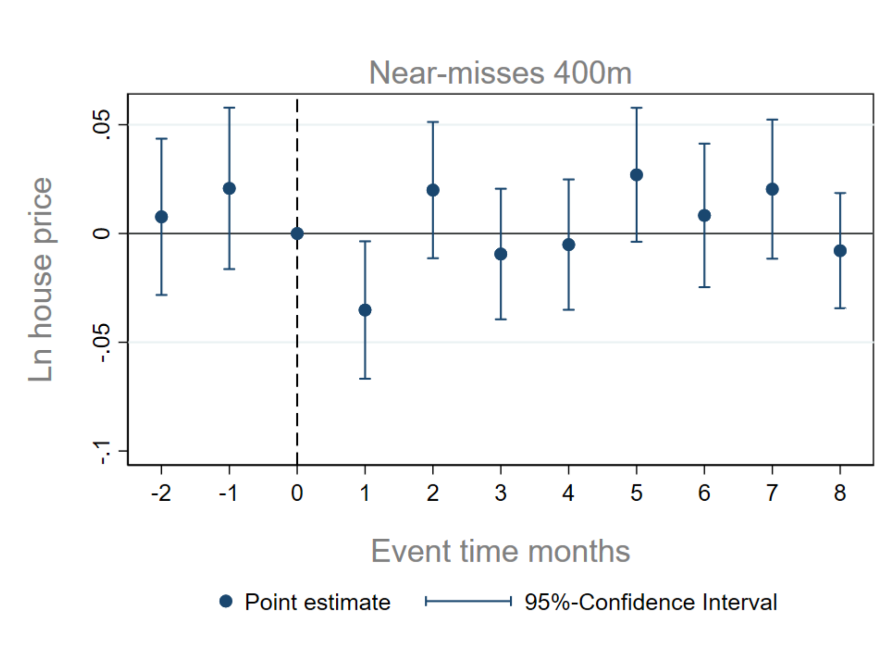



Figure 8: Near–misses (400m) vs. non Near–misses. Notes: The figure plots event time coefficients from estimation of equation 9 with Near–misses as the treatment group on the 2007–2019 house price panel. We use the eleven biggest floods occurring between 2007–2019. Each point illustrates the average effect after e.g. 1–2 months (=2 on the x-axis). The bars show the 95 percent confidence interval. The vertical axis measures ln house prices. The reference category is the time window of -1 - 0 months before the flood. Endpoints are binned.

the property actually changes ownership. Often, the selling price is agreed upon several weeks

[32]In our sample, 3,375 claims occurred in non-hazard zones and only 207 in hazard zones.

Table 4: Event study based on Near-misses

| | *Dependent v.:* Ln price sqm, real | | |
|---|---|---|---|
| | (1) NM300 | (2) NM400 | (3) NM500 |
| $\text{miss}^{300m} \times \text{flood}^{+1}$ | −0.035** (0.014) | | |
| $\text{miss}^{300m} \times \text{flood}^{+2}$ | 0.017 (0.018) | | |
| $\text{miss}^{300m} \times \text{flood}^{+3}$ | −0.019 (0.019) | | |
| $\text{miss}^{300m} \times \text{flood}^{+4}$ | 0.004 (0.016) | | |
| $\text{miss}^{400m} \times \text{flood}^{+1}$ | | −0.038*** (0.013) | |
| $\text{miss}^{400m} \times \text{flood}^{+2}$ | | 0.016 (0.015) | |
| $\text{miss}^{400m} \times \text{flood}^{+3}$ | | −0.011 (0.021) | |
| $\text{miss}^{400m} \times \text{flood}^{+4}$ | | −0.010 (0.014) | |
| $\text{miss}^{500m} \times \text{flood}^{+1}$ | | | −0.025* (0.014) |
| $\text{miss}^{500m} \times \text{flood}^{+2}$ | | | 0.014 (0.012) |
| $\text{miss}^{500m} \times \text{flood}^{+3}$ | | | −0.007 (0.014) |
| $\text{miss}^{500m} \times \text{flood}^{+4}$ | | | −0.002 (0.014) |
| *Constant* | 9.556*** (1.505) | 9.187*** (1.676) | 9.693*** (1.889) |
| Weekday FE | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ |
| Zip code × year FE | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ |
| Observations | 18,701 | 19,290 | 19,707 |

*Note:* Dependent variable is the Ln sqm. price. Results for a coefficient from estimation equation (9), standard errors in parentheses are clustered at the municipality level. The reference are the months -3 - 0 before and > 5 months after the flood. In each specification, we use a buffer excluding a radius of 300m. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

before this date, with the interim phase used to secure financing, drawing up the paperwork etc. If this phase takes around one months, then the peak at $miss \times flood^{+1}$ can be considered consistent with an immediate effect of a flood event on the contract price.

The definition of Near–misses is somewhat arbitrary, and buyers may disagree about what constitutes a close call in terms of a narrowly missed flood damage. To learn more about the sensitivity of our results to the specification of the Near-miss dummy, we estimate equation (9) for Near–misses computed using distance thresholds between 400–600 m. Table 4 provides the results obtained from estimating equation (9) using $< 400m$, $< 500m$ and $< 600m$ radius Near–misses as the treatment group and non–Near–misses (i.e. houses which are not damaged and further away, excluding a buffer of 300 m radius) as the control group. The reference are all other months which are not explicitly shown. Likewise, there is a significant negative effect after one month in all specifications, table 4 column 1 - 3.

Our findings are consistent with Beltrán et al. (2018a), who show that near–missed inland properties (in terms of being located close to an inundated zone) experience a discount in the immediate aftermath of inland flooding. Because we exclude damages, we can interpret the negative discount on housing value as an information effect. After a damage occurs, prospective buyers of a neighboring property will see the flood damage when inspecting the house they wish to buy. Because the hazard zones are very imprecise, knowing that a nearby property was damaged presumably leads to an update of the risk assessment, beyond the mean zonal risk (which is very low as most houses are never damaged, even within hazard zones). Buyers might learn that the property of interest is located at a risky place. In line with Tinsley et al. (2012) who study Hurricane experience in the US, we learn that Near-misses might actually suggest vulnerability to a potential negative outcome.

To strengthen our conclusion that home buyers consider the near–missed houses as being at danger, we further calculate whether the evaluation of a Near-miss is evaluated above ("higher Near-miss") or below/equal ("Lower Near-miss") relative to the damaged property. One would expected that houses located above damaged properties are considered to be safer and houses at an evaluation below to be perceived as riskier. Table 5 provides the results for 500m Near-misses.[33] Column (1) shows the results for lower/ and equally evaluated Near-misses and column (2) for higher Near-misses. These results support the idea that a possible or negative feeling of security does indeed depend on the evaluation of the house. There is a significant negative effect for lower / equally evaluated near-miss but in contrast, we see a significant and positive effect after one to two months after a flood for higher near-misses compared to lower near-misses.

There is a certain inaccuracy in our specifications as to when a flood effect is reflected in the data. This inaccuracy can be explained by the fact that there is not an exact time span between price determination and the notary appointment (i.e. our transaction date). Depending on the buyer and seller, it may well be that a financially strong buyer only needs a month, whereas another buyer needs more time to organize financing.

However, it turns out that the overall effect is very short (between one (table 4) and three months after the flood (table 5)). One could argue that or findings support the presence of an

[33] We use the 500 m Near-miss radius to increase sample size for higher and lower Near-misses.

Table 5: Higher / lower Near-miss DiD results

| | *Dependent v.:* Ln price sqm, real | |
|---|---|---|
| | (1) NM500, lower | (2) NM500, higher |
| Lower miss$^{500m}$ × flood$^{+1}$ | −0.023 | |
| | (0.025) | |
| Lower miss$^{500m}$ × flood$^{+2}$ | −0.002 | |
| | (0.022) | |
| Lower miss$^{500m}$ × flood$^{+3}$ | −0.034* | |
| | (0.019) | |
| Lower miss$^{500m}$ × flood$^{+4}$ | −0.014 | |
| | (0.023) | |
| Higher miss$^{500m}$ × flood$^{+1}$ | | −0.023 |
| | | (0.017) |
| Higher miss$^{500m}$ × flood$^{+2}$ | | 0.028** |
| | | (0.013) |
| Higher miss$^{500m}$ × flood$^{+3}$ | | 0.019 |
| | | (0.014) |
| Higher miss$^{500m}$ × flood$^{+4}$ | | 0.010 |
| | | (0.017) |
| *Constant* | 9.708*** | 9.669*** |
| | (1.877) | (1.882) |
| Weekday FE | ✓ | ✓ |
| Month FE | ✓ | ✓ |
| Zip code × year FE | ✓ | ✓ |
| Controls | ✓ | ✓ |
| Observations | 19,707 | 19,707 |

*Note:* Dependent variable is the Ln sqm. price. Results for a coefficient from estimation equation (9) where we seperate higher and lower /equal evaluation near–misses. Standard errors in parentheses are clustered at the municipality level. The reference are the months -3 - 0 before and > 5 months after the flood. In each specification, we use a buffer excluding a radius of 300m. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

availability bias. But potentially, owners will organize and carry out repairs, paid for by the building insurance. Once these repairs are completed, prospective buyers have no way of knowing that there was a flood damage nearby, unless the buyer explicitly informs them about this. However, they have little incentives to do so. In this sense, our results do not necessarily require a deviation from rationality as in the availability bias literature, but they could simply be driven by the temporal visibility of the signal.

### 5.3 Robustness checks

To learn more about the sensitivity of our results to the specification of the near-miss dummy, we further provide additional estimates for equation (9) for Near–misses computed using distance thresholds between 700–1000 m.[34] Figure 9 illustrates the event study results. There seems to be a negative effect one month after the flood, but the effects are not significant. It can thus be suggested that it depends very much on how close you are to a damaged house. The further away, the more likely one will no longer find any effect.

[34]Sample size below 300 m is to low.

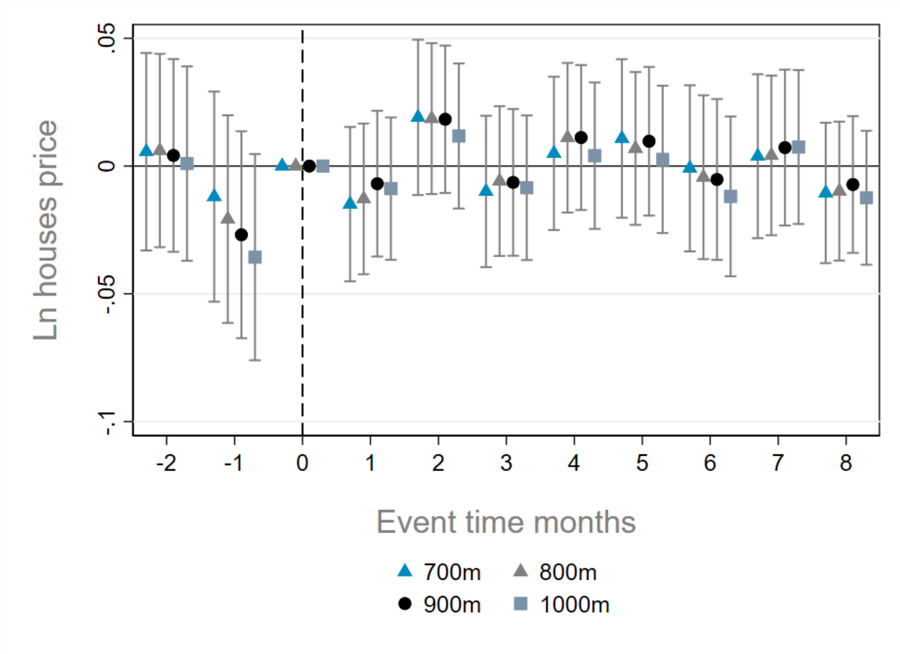



Figure 9: Flood effect 2007 – 2019 for different Near-miss groups. Notes: The figure plots event time coefficients from estimation of equation 9 with different near–misses as the treatment group (700–1000m) on the 2007–2019 house price panel. Each color represents coefficients of a separate estimation and each point illustrates the average effect after e.g. 1–2 months (=2 on the x-axis). The bars show the 95 percent confidence interval. Standard errors are clustered at the municipality level. The vertical axis measures ln house prices. The reference category is the time window of -1 - 0 months before the flood. Endpoints are binned.

In our main DiD specifications, we include 12 months fixed effects but not months-year fixed effects as there would be an overlap with our event study coefficients. One could argue, that our results could thus be bias by year-specific trends. Thus, we further provide estimates with month-of-year fixed effects. What is crucial for the identification of the flood effect in conjunction with month–of–year fixed effects is that the floods did not occur on the first day of a a calendar month, such that they are not absorbed by the month–year dummies, see figure 3. Table A.5 presents the results, which are robust.

One important referendum related to housing value took place in September 2014. There was a cantonal referendum on the submission of a new planning and building law. Residents had to decide whether there should be a minimum share of reasonably priced housing.[35] The referendum was accepted and municipalities should reserved a minimum proportion of specified building zones for low-cost apartments. We include a dummy, which is one if the transaction took

[35]The submission template "Determination of minimum share of affordable housing" is intended to expand the scope of action of municipalities in promoting low-cost housing construction and to create the necessary legal basis. An amendment to the planning and construction act is intended to allow municipalities to impose low-cost housing units in a given area, while at the same time improving their structural potential (Canton of Zurich, 2014b).

place after the referendum. Table A.6 presents the results. The referendum has a significant and negative effect on house prices, see table A.6. The main DiD estimation results do not change.

# 6 Concluding remarks

Negative effects on housing prices in the aftermath of disastrous hurricanes and floods in the US are well established. Mandatory insurance for the most risky flood zones can explain a negative effect on its own. However, less is known about a setting where socialized building insurance exist. In addition, most of the existing studies use floodplain maps only as a flood risk measure, suffering from problems, which should not be ignored. Our study utilizes both, flood maps as well as insurance claims to determine the effect of the floods between 2007–2019 in the canton of Zurich, Switzerland using not only hazard zones as a treatment but also Near–misses. This allows us to identify very clearly whether a potential effect of floods on housing value is to informational updating or due to actual damages.

To summarize, the first difference results of being located in a hazard zone is negative and significant. Houses located in hazard zones sell at a discount relative to houses without flood risk (H1). Although there is social insurance, we see that the uninsurable costs of flooding are reflected in house prices

Exploring the influence of public information on designated hazard zones, reveals that the effect on house prices varies with the degree of risk. When home owners learn, that they are located in a "safe" zone, we find a positive and significant effect (H2). Being located in hazard zone in turn does not seem to have any effect. Potentially, the cantonal introduction of hazard maps is not sufficiently capitalized into housing prices.

Results for our first DiD specification using hazard maps as the treatment category violates SUTVA, as only some actually damaged houses are located in hazard zones and we do not find an effect in the aftermath of a flood. A more accurate strategy to assess the information effect of floods is to calculate Near–misses, i.e., housing properties closely located to actual damages (but not damaged themselves). In this DiD specifications, there is a drop shortly after a flood has occurred, suggesting that there is evidence for informational updating (H3). We find that immediately after the flood, near–missed housing values are sold for substantially less than equivalent properties further away. The cantonal government of Zurich government decided in 2017 to implement a new project against extreme flooding of the river Sihl, which is expected to cost around 130 million CHF and would be completed in 2023 at the earliest (Amt fuer Abfall, Wasser, Energie und Luft, 2017). The estimates of our study provide valuable information necessary in the context of cost–benefit analyses of public investments in flood protection measures or of mandatory insurance schemes, in which the price depends on risk. Clearly, people need information about flood risk to be consider in their locational choice. Existing hazard maps are a first step, but they are not sufficient. We learn that people are somewhat rational as flood risk is priced into housing, despite socialized insurance. However, the effect is only temporary.

Our results are partially in line with the literature (Bin and Landry, 2013; Atreya et al., 2013b; Gallagher, 2014). However, the time horizon of studied events as well as the setting is very different. "Forgetting" related to house prices of large scale events in the US, i.e., hurricanes and related floods, takes from six (Bin and Landry, 2013) to eight years (Atreya et al., 2013b) and up to nine years if the outcome of interest is insurance take up (Gallagher, 2014). The setting in the canton of Zurich is quite different. There exists social insurance and the floods are very unlike compared to the US flood events in terms of caused damage. There remains work to be done assessing detailed geological characteristics of river floods and the link to housing and land prices. What is the critical threshold in terms of damages, such that a flood is of consequence for real estate prices? In addition, "forgetting" of past flood events is rather fast, compared to tremendous hurricanes in the US. It would be a fruitful task for future research to investigate whether social building insurance alone can explain this fast and persistent "forgetting".

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# Appendix

## A.1 Literature review

The following table provides a review of the previous literature. It provides the year of publication, the place and sample period, the main methods used, the dependent variable, the proxy for flood risk and the role of insurance. The column "Effect" describes the main effect shown in the paper, or lack thereof if not statistically significant.

| Author | Year | Country | Location | Method used | Dependent variable | Flood risk | Insurance | Effect | Time in years | Specific flood? |
|---|---|---|---|---|---|---|---|---|---|---|
| Barnard (1978) | 1978 | US | Ralston Creek | Standard hedonic price model | Housing prices | 100-year floodplains | NA | urban expansion has increased the runoff and flood hazard in the Ralston Creek watershed | 1973 | No |
| MacDonald et al. (1987) | 1987 | US | Monroe,Louisiana | Theoretical model and hedonic price regression | Housing prices | Probability of flooding determined using the different levels from the Flood Insurance Rate Maps | Flood insurance premiums reflect flood risk of the area because they are based on elevation | negative effect | 1985 | No |
| Skantz and Strickland (1987) | 1987 | US | Texas | Standard hedonic price model and DiD | Housing prices | 100-year floodplains | NFIP flood insurance | Increase in flood insurance rate one year after the flood | 1977 - 1981 | Yes, 1979 |
| Donnelly (1989) | 1989 | US | WI | Standard hedonic price model | Housing sales dataă | 100 year floodplain | NFIP flood insurance | negative effect | 1983 - 1985 | No |
| Shilling et al. (1989) | 1989 | US | Lousiana | Standard hedonic price model | Housing prices | 100 year floodplain | NFIP flood insurance | negative effect | 1982 - 1984 | No |
| Bialaszewski and Newsome (1990) | 1990 | US | Homewood, Alabamaăand Monroe, Louisiana | Standard hedonic price model | Housing prices | 100-year floodplains | NFIP flood insurance | negative effect for Monroe | 1987 - 1989 | No |
| Holway and Burby (1990) | 1990 | | | | | | | | | |
| MacDonald et al. (1990) | 1990 | US | Monroe, Louisiana | Standard hedonic price model | Housing prices | 100 year floodplain | NFIP flood insurance | negative effect | 1988 | No |
| Speyrer and Ragas (1991) | 1991 | US | New Orleans, Louisiana | Linear and semi-logarithmic regressions | Selling prices | 100-year floodplain | NFIP flood insurance | negative effect | 1971-1986 | 1978, 1980, and 1983 |
| Bartosova et al. (2000) | 1999 | US | WI | Standard hedonic price model | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | negative effect | 1995 - 1998 | Flood in 1997 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Fridgen et al. (1999) | 1999 | US | ND,MI | Standard hedonic price model | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | negative effect for 100 year flood plains | 1995-1998 | Flood 1997 |
| Harrison et al. (2001) | 2001 | US | Alachua County, Florida | Hedonic pricing techniques | Housing prices | 100-year floodplain | NFIP flood insurance | negative effect | 1980Ű1997 | No |
| Shultz and Fridgen (2001) | 2001 | US | Fargo Moorhead | Standard hedonic price model | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | flood insurance premiums were determined to account for approximately 81 percent of price depreciation | 1995 - 1998 | No |
| Dei-Tutu and Bin (2002) | 2002 | US | NC | Standard hedonic price model | Housing prices | 100-year floodplain | NFIP flood insurance | negative effect | 1998 - 2002 | Flood in 1999 |
| Eves (2002) | 2002 | Australia | Sydney | Standard hedonic price model | Housing prices | 100-year floodplain | No insurance | negative effect | 1994 - 2000 | Flood 1990 |
| Zhai et al. (2003) | 2003 | Japan | Tokai region | cross-sectional analysis, and hedonic approach based panel analysis | Land prices | actual damaged houses | | land prices in flood-prone areas are lower and have less variance than in other areas | | 2000 Tokai flood in Japan |
| Bin and Polasky (2004) | 2004 | US | North Carolina | Standard hedonic price model, DiD | Housing prices | 100 year floodplain | NFIP flood insurance | negative effect , bigger effect directly after the flood | 1992 - 2002 | Flood in 1999, after Hurricane Floyd |
| Bin (2004) | 2004 | US | North Carolina | Hedonic price model, Semi-parametric regression | Housing prices | 100-year floodplains | NFIP flood insurance | | 2000 - 2002 | No |
| Troy and Romm (2004) | 2004 | US | California | DiD spatial hedonic model | Housing prices | floodplain disclosure under AB 1195 | | negative effect | 1996 - 2000 | floodplain disclosure under AB 1195 |
| Hallstrom and Smith (2005) | 2005 | US | FL | DiD spatial hedonic model | Housing prices | 100-year floodplains | NFIP flood insurance | negative effect | 21 years, | Hurrican Andrew 1992 |
| Bin and Kruse (2006) | 2006 | US | North Carolina | Standard hedonic price model | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | negative effect | 2002 - 2004 | No |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Lamond and Proverbs (2006) | 2006 | England | Barlby, North Yorkshire | Semi-logarithmic regression | Housing prices | UK flood maps, Flood dummy | voluntary insurance | no significant long-term impact on prices of property in the floodplain, in the short term prices increased less than in the rest of the market | 2000-2005 | Floods in 2000 and 2001 |
| Baade et al. (2007) | 2007 | US | Miami, New Orleans | MLE | Taxable sales | not relevant | not relevant | short-term positive effect on the Miami economy | 1987 Ű 2004 | Hurricane Andrew, Hurricane Katrina, Rodney King riots |
| Lamond et al. (2007) | 2007 | England | Bewdley, Worcestershire | Repeated sales model | Housing prices | Before and after 2000 floods | voluntary insurance | Prices are discounted 7 | | |
| Daniel et al. (2007) | 2007 | Netherlands | near Meuse river | Standard hedonic price model, DiD | Housing prices | Transition plains | N/A | local housing markets in the Netherlands are sensitive to flood risk | 1990 - 2004 | Floods of Meuse river |
| Morgan (2007) | 2007 | US | Florida | Standard hedonic price model | Housing prices | 100-year floodplains | NFIP flood insurance | positive effect, flood event adjusts the market downward | 2000-2006 | Hurricane Ivan |
| Bin et al. (2008a) | 2008 | US | North Carolina | Standard hedonic price model, spatial autoregressive model | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | negative effect | 2000-2004 | No |
| Bin et al. (2008b) | 2008 | US | North Carolina | Spatial autoregressive hedonic model | Housing prices | 100 year floodplain | NFIP flood insurance | negative effect | 1996 - 2002 | No |
| Burningham et al. (2008) | 2008 | England | | Logistic regression analysis of the factors predicting the likelihood of awareness of flood risk | Respondents awareness that property was in a flood risk area | | | Social class has the most influence on predicting awareness of flood risk, followed by flood experience and then length of time in residence | - | Severe flood events in 1998 and 2000 |
| Pope (2008) | 2008 | US | North Carolina | Standard hedonic price model, DiD | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | negative effect, buyer and seller are differently informed | 1995 - 1996 | No |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Daniel et al. (2009) | 2009 | US | | Meta-study | Housing prices | different specifications | NFIP flood insurance | overall negative effect | | |
| Daniel et al. (2009) | 2009 | US | whole US | Meta-study | Housing price estimates | 100-year and 500-year floodplains | NFIP flood insurance | negative effect, avaerage price of an otherwise similar house of Ű0.6%. | 1990 - 2004 | No, several flood events |
| Kousky (2010) | 2010 | US | Missouri | Standard hedonic price model, DiD | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | | 1979 - 2006 | 1993 flood on the Missouri and Mississippi rivers |
| Lamond et al. (2010) | 2010 | England | | Variation of the repeat sales index model | Housing prices | Four risk classes significant (S), moderate (M), low (L) and outside the floodplain (O) | In the UK, flood risk has been included as standard within the general domestic all risks insurance policy since the late 1960s. However, different revisions to the principles after 2000 allow for removal of cover from high risk properties and pricint to risk. | Flood impacts on property prices are small and temporary | 2000-2006 | Flood events of autumn 2000 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| McKenzie and Levendis (2010) | 2010 | US | New Orleans | Hedonic price regression, flooded vs non-flooded subset, pre- vs post- Katrina | Housing prices | Elevation (in foots) value in flood-prone areas and areas not subject to flooding, pre- and post-Katrina. | No information found (see SAB comment) | positive effect of elevation , which increased from 1.4% to 4.6% for flooded areas after Katrina. | 2.5, January 2004-August 2006 | Hurricane Katrina |
| Michel-Kerjan and Kousky (2010) | 2010 | US | Florida | OLS regression | Demand for flood insurance | 100-year and 500-year floodplains | NFIP flood insurance | Analysis of flood insurance market | 2000 - 2005 | No |
| Posey and Rogers (2010) | 2010 | US | Missouri | Standard hedonic price model, correction for autoregressive errors | Housing prices | 100-year floodplains | NFIP flood insurance | located in a flood zone reduces the value of a property by about 8.6%, including both direct and indirect effects | 2000 | No |
| Samarasinghe and Sharp (2010) | 2010 | New Zealand | North Shore City | Spatial autoregressive hedonic model | Housing prices | 100-year floodplains | No mandatory insurance | | | |
| Pryce et al. (2011) | 2011 | | | Theoretical model | | | | | | |
| Atreya and Ferreira (2012) | 2012 | US | Georgia | DiD | Housing prices | 100-year and 500-year floodplains, actual inundated area | NFIP flood insurance | negative effect, more pronounced by affected areas | 1985 -Ű2010 | 1994 flood in Albany |
| Atreya et al. (2013a) | 2012 | US | Georgia | DiD | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | Negative, short lived effect | 1985 - 2010 | 1994 |
| Atreya et al. (2013b) | 2013 | US | Dougherty County, Georgia | DiD | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | negative effect (significant for the 100y FP) | 1985 - 2004 | 1994 Şflood of the centuryŤ |
| Atreya et al. (2013b) | 2013 | US | Georgia | DiD | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | significant increase in the discount for properties in the 100-year floodplain immediately after the flood. | 1985 - 2004 | 1994, the Flint River overran |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Bin and Landry (2013) | 2013 | US | Pitt County, North Carolina | DiD | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | Negative effect, Change in risk valuation after significant flooding events found. | 1992 - 2008 | Hurricanes Fran 1996 and Floyd 1999 |
| Bin and Landry (2013) | 2013 | US | Pitt County, NorthCarolina | DiD | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | Prior to Hurricane Fran, we detect no market risk premium for presence in a flood zone, but we find significant price differentials after significant flooding events | 1992 - 2008 | Hurricane Fran and Hurricane Floyd |
| Petrolia et al. (2013) | 2013 | US | U.S. Gulf Coast and Floridas Atlantic Coast | Experimental survey | Flood insurance purchase decisions | 100-year and 500-year floodplains | NFIP flood insurance | risk aversion over the loss domain, perceived expectations of hurricane damage, eligibility for disaster assistance, and credibility of insurance providers positively and significantly correlates with the decision to purchase a flood policy | | |
| Rambaldi et al. (2013) | 2013 | Australia | Brisbane | Standard hedonic price model | Housing prices | 100 year floodplain | residences are able to obtain commercially available flood insurance | property-price discounting of 5.5 percent per metre below the defined flood level | | |
| Small et al. (2013) | 2013 | Australia | Rockhampton | Mail survey of flood-affected properties and comparison to market | Descriptive analysis | | N/A | larger negative discount is not supported in the data | | 2011 Rockhampton floods |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Turnbull et al. (2013) | 2013 | US | Louisiana, Baton Rouge metropolitan area | search model to the flood hazard situation; system estimation framework | Housing price and liquidity | 100-year and 500-year floodplains | NFIP flood insurance | flood risks are capitalized into both house price and liquidity | 1984 - 2005 | |
| Gallagher (2014) | 2014 | US | Entire country | Event study framework | insurance policies per capita | 100-year and 500-year floodplains | NFIP flood insurance | insurance take-up spikes the year after a flood and then steadily declines to baseline | 1990Ű2007 | Several floods |
| Husby et al. (2014) | 2014 | Netherlands | | Dynamic DiD | Population growth | Areas affected by the 1953 flood | | Long-term effects on population growth were most likely not directly related to the flood in 1953, the positive long-term effects found were instead due to the policy interventions following the flood | 1947-2000 | Great North Sea Flood of 1953 and the construction of the Deltaworks |
| Atreya and Ferreira (2015) | 2015 | US | | DiD | Housing prices | the flood inundation map, 100-year and 500-year floodplains | | the price discount for properties in the inundated area is substantially larger than in comparable properties in the floodplain | | |
| Hill (2015) | 2015 | US | New York | DiD | Housing prices | 100-year and 500-year floodplains, newly assigned flood zones | NFIP flood insurance | sale price of a property newly placed in any flood zone after 2015 decreases by 8.6 percent on average | 2003 - 2015 | Hurricane Sandy 2012 |
| Belanger and Bourdeau-Brien (2018) | 2016 | England | whole UK | Linear mixed effects model / hierachical model | Housing prices | UK flood maps, Flood dummy | Insure price insurance policies according to individual property flood risk | negative effect | 1995 - 2015 | No |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Meldrum (2016) | 2016 | US | Boulder County, Colorado | Hedonic price estimation and non-parametric matching estimation | Housing prices | | NFIP flood insurance | strong price effect associated with floodplain-designation for condominiums but no price differential for standalone properties | 1995 - 2012 | No |
| Bakkensen and Barrage (2017) | 2017 | US | North Carolina, Rhode Island | Door-to-door survey campaign and theoretical model | Fl?ood risk perceptions | not relevant | NFIP flood insurance | selection into coastal homes is driven by both lower risk perceptions and higher coastal amenity values | 2016 | No |
| Beltrán et al. (2018b) | 2018 | | | Meta-study, 37 studies and 349 point estimates | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | price discount lies anywhere between -75.5 to a +61.0 | | |
| Atreya and Czajkowski (2019) | 2019 | US | Galveston County, TX | Standard hedonic model, FE model | Housing prices | 100-year and 500-year floodplains | NFIP flood insurance | hedonic price premium is dependent upon the distance to the coast | 2001 - 2010 | No |

## A.2 Descriptives

Table A.2: Summary Statistics

| | Mean | S.D. | Min. | Max. |
|---|---|---|---|---|
| Ln (Price) | 7.617 | 0.814 | −0 | 11 |
| damage | 0.054 | 0.225 | 0 | 1 |
| Ln (rooms) | 1.629 | 0.243 | 0 | 4 |
| Ln (size) | 6.357 | 0.789 | 3 | 13 |
| Ln (age) | 3.754 | 1.020 | 0 | 7 |
| Ln (distwater) | 5.199 | 0.923 | −1 | 7 |
| Ln (distZH) | 9.684 | 0.645 | 6 | 11 |
| Ln (distforest) | 5.209 | 0.898 | −0 | 8 |
| Ln (radiation) | 4.912 | 0.034 | 5 | 5 |
| Ln (tax) | 4.659 | 0.140 | 4 | 5 |
| Ln (vismaxdist) | 11.079 | 0.778 | 7 | 12 |
| Unkown zone | 0.000 | 0.020 | 0 | 1 |
| Single familiy | 0.589 | 0.492 | 0 | 1 |
| Business | 0.003 | 0.054 | 0 | 1 |
| Mixed | 0.258 | 0.437 | 0 | 1 |
| Munic. district | 0.000 | 0.019 | 0 | 1 |
| Wood | 0.001 | 0.024 | 0 | 1 |
| Farming | 0.033 | 0.179 | 0 | 1 |
| Reserve | 0.001 | 0.038 | 0 | 1 |
| Public | 0.000 | 0.017 | 0 | 1 |
| No–building zone | 0.002 | 0.045 | 0 | 1 |
| Multiple familiy zone | 0.112 | 0.315 | 0 | 1 |
| miss$^{500m}$ | 0.341 | 0.474 | 0 | 1 |
| miss$^{600m}$ | 0.395 | 0.489 | 0 | 1 |
| miss$^{700m}$ | 0.444 | 0.497 | 0 | 1 |
| Lower miss$^{500m}$ | 0.161 | 0.368 | 0 | 1 |
| Lower miss$^{600m}$ | 0.186 | 0.389 | 0 | 1 |
| Lower miss$^{700m}$ | 0.206 | 0.405 | 0 | 1 |
| Higher miss$^{500m}$ | 0.180 | 0.384 | 0 | 1 |
| Higher miss$^{600m}$ | 0.210 | 0.407 | 0 | 1 |
| Higher miss$^{700m}$ | 0.238 | 0.426 | 0 | 1 |
| Buffer 500 - 1000m | 0.220 | 0.415 | 0 | 1 |

| | Mean | S.D. | Min. | Max. |
|---|---|---|---|---|
| Buffer 600 - 1000m | 0.166 | 0.372 | 0 | 1 |
| Buffer 700 - 1000m | 0.117 | 0.321 | 0 | 1 |
| $\text{flood}^{+1}$ | 0.070 | 0.255 | 0 | 1 |
| $\text{flood}^{+2}$ | 0.065 | 0.246 | 0 | 1 |
| $\text{flood}^{+3}$ | 0.069 | 0.254 | 0 | 1 |
| $\text{flood}^{+4}$ | 0.064 | 0.245 | 0 | 1 |
| $\text{flood}^{+5}$ | 0.063 | 0.244 | 0 | 1 |
| $\text{flood}^{+6}$ | 0.063 | 0.244 | 0 | 1 |
| $\text{flood}^{+7}$ | 0.057 | 0.232 | 0 | 1 |
| $\text{flood}^{+8}$ | 0.058 | 0.234 | 0 | 1 |
| $\text{flood}^{+9}$ | 0.916 | 0.278 | 0 | 1 |
| $\text{flood}^{-0}$ | 0.066 | 0.248 | 0 | 1 |
| $\text{flood}^{-1}$ | 0.062 | 0.241 | 0 | 1 |
| $\text{flood}^{-2}$ | 0.064 | 0.245 | 0 | 1 |
| $\text{flood}^{-3}$ | 0.061 | 0.240 | 0 | 1 |
| Hazard | 0.111 | 0.314 | 0 | 1 |
| Hazard low | 0.093 | 0.291 | 0 | 1 |
| Hazard medium | 0.017 | 0.131 | 0 | 1 |
| mapintro | 0.930 | 0.255 | 0 | 1 |
| mandatory | 0.523 | 0.499 | 0 | 1 |
| weekday | 3.145 | 1.462 | 0 | 6 |
| Month | 6.716 | 3.373 | 1 | 12 |
| Zip codes | 135.969 | 74.623 | 1 | 256 |
| Year | 2012.926 | 3.771 | 2007 | 2019 |
| Total observations | 36118 | | | |

## A.3 GVZ insurance

Table A.3: GVZ claim statistic on a yearly base

| Year | Annual number of building damage | Annual building damage [CHF] | Average amount of damage per claim [CHF] |
|---|---|---|---|
| 2006 | 132 | 954,323.0 | 7,230.0 |
| 2007 | 576 | 6,050,587.0 | 10,504.0 |
| 2008 | 368 | 3,903,027.0 | 10,606.0 |
| 2009 | 274 | 1,780,504.0 | 6,498.0 |
| 2010 | 215 | 1,946,096.0 | 9,052.0 |
| 2011 | 382 | 3,661,002.0 | 9,584.0 |
| 2012 | 297 | 2,397,430.0 | 8,072.0 |
| 2013 | 498 | 5,814,337.0 | 11,675.0 |
| 2014 | 335 | 3,756,345.0 | 11,213.0 |
| 2015 | 505 | 6,560,613.0 | 12,991.0 |
| 2016 | 233 | 1,966,285.0 | 8,439.0 |

Notes: The table show the aggregated values of GVZ insurance claims per year 2006 – 2017. Only flood damage with the status "completed", "pending" or "reactivated" were taken into account. The damage amounts include the deductible (i.e. the so-called gross damage).

## A.4 Additional Results

Table A.4: Near-miss DiD results

| | *Dependent v.:* Ln price sqm, real | | |
|---|---|---|---|
| | (1) Hazard, 2 cat. | (2) Low Hazard, 3 cat. | (3) Med. Hazard, 3 cat. |
| hazard × flood$^{+1}$ | −0.015 | | |
| | (0.037) | | |
| hazard × flood$^{+2}$ | −0.016 | | |
| | (0.025) | | |
| hazard × flood$^{+3}$ | −0.033 | | |
| | (0.023) | | |
| hazard × flood$^{+4}$ | −0.029 | | |
| | (0.018) | | |
| hazard=2 × flood$^{+1}$ | | −0.009 | |
| | | (0.042) | |
| hazard=2 × flood$^{+2}$ | | −0.032 | |
| | | (0.026) | |
| hazard=2 × flood$^{+3}$ | | −0.040 | |
| | | (0.029) | |
| hazard=2 × flood$^{+4}$ | | −0.037 | |
| | | (0.024) | |
| hazard=3 × flood$^{+1}$ | | | −0.074 |
| | | | (0.050) |
| hazard=3 × flood$^{+2}$ | | | 0.066 |
| | | | (0.051) |
| hazard=3 × flood$^{+3}$ | | | −0.007 |
| | | | (0.046) |
| hazard=3 × flood$^{+4}$ | | | −0.002 |
| | | | (0.054) |
| *Constant* | 9.874*** | 9.885*** | 9.847*** |
| | (1.566) | (1.591) | (1.582) |
| Weekday FE | ✓ | ✓ | ✓ |
| Month FE | ✓ | ✓ | ✓ |
| Zip code × year FE | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ |
| Observations | 21,514 | 21,514 | 21,514 |

Notes: Dependent variable is the Ln sqm. price. Results from estimation equation (7), standard errors in parentheses are clustered at the municipality level. We restrict the sample to sales, where the hazard map was already availble at the transaction time. Column (1) shows results using two hazard categories (hazard and non–hazard) and column (2) and (3) print results using three categories (low and medium). No hazard is in all specifications the ref. category and the time reference are the months -3 - 0 before and > 5 months after the flood. We do not control for distance for water due to collinarity with the hazard zone variable. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

## A.5 Robustness results

Table A.5: Robustness Near-miss DiD results incl. month-of-year FE

| | *Dependent v.:* Ln price sqm, real | | | |
|---|---|---|---|---|
| | (1) NM300, all | (2) NM400, all | (3) NM500, lower | (4) NM500, higher |
| $\text{miss}^{300m} \times \text{flood}^{+1}$ | $-0.036^{**}$ | | | |
| | (0.014) | | | |
| $\text{miss}^{300m} \times \text{flood}^{+2}$ | 0.014 | | | |
| | (0.020) | | | |
| $\text{miss}^{300m} \times \text{flood}^{+3}$ | $-0.034^{*}$ | | | |
| | (0.019) | | | |
| $\text{miss}^{300m} \times \text{flood}^{+4}$ | 0.001 | | | |
| | (0.017) | | | |
| $\text{miss}^{400m} \times \text{flood}^{+1}$ | | $-0.043^{***}$ | | |
| | | (0.014) | | |
| $\text{miss}^{400m} \times \text{flood}^{+2}$ | | 0.010 | | |
| | | (0.013) | | |
| $\text{miss}^{400m} \times \text{flood}^{+3}$ | | $-0.025$ | | |
| | | (0.020) | | |
| $\text{miss}^{400m} \times \text{flood}^{+4}$ | | $-0.014$ | | |
| | | (0.014) | | |
| Lower $\text{miss}^{500m} \times \text{flood}^{+1}$ | | | $-0.018$ | |
| | | | (0.024) | |
| Lower $\text{miss}^{500m} \times \text{flood}^{+2}$ | | | $-0.007$ | |
| | | | (0.021) | |
| Lower $\text{miss}^{500m} \times \text{flood}^{+3}$ | | | $-0.044^{***}$ | |
| | | | (0.016) | |
| Lower $\text{miss}^{500m} \times \text{flood}^{+4}$ | | | $-0.014$ | |
| | | | (0.022) | |
| Higher $\text{miss}^{500m} \times \text{flood}^{+1}$ | | | | $-0.020$ |
| | | | | (0.020) |
| Higher $\text{miss}^{500m} \times \text{flood}^{+2}$ | | | | $0.029^{**}$ |
| | | | | (0.014) |
| Higher $\text{miss}^{500m} \times \text{flood}^{+3}$ | | | | 0.013 |
| | | | | (0.014) |
| Higher $\text{miss}^{500m} \times \text{flood}^{+4}$ | | | | 0.009 |
| | | | | (0.018) |
| *Constant* | $9.675^{***}$ | $9.286^{***}$ | $9.869^{***}$ | $9.825^{***}$ |
| | (1.574) | (1.702) | (1.898) | (1.905) |
| Weekday FE | ✓ | ✓ | ✓ | ✓ |
| Month-Year FE | ✓ | ✓ | ✓ | ✓ |
| Zip code × year FE | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Observations | 18,701 | 19,290 | 19,707 | 19,707 |

*Note:* Dependent variable is the Ln sqm. price. Results for a coefficient from estimation equation (9) including month-of-year FE, standard errors in parentheses are clustered at the municipality level. The reference are the months -3 - 0 before and > 5 months after the flood. In each specification, we use a buffer excluding a radius of 300m. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.

Table A.6: Robustness Near-miss DiD results incl. referedum

| | *Dependent v.:* Ln price sqm, real | | | |
|---|---|---|---|---|
| | (1) NM300, all | (2) NM400, all | (3) NM500, lower | (4) NM500, higher |
| After 14 refer. | −0.054*** | −0.039*** | −0.053*** | −0.055*** |
| | (0.003) | (0.003) | (0.002) | (0.002) |
| $\text{miss}^{300m} \times \text{flood}^{+1}$ | −0.036** | | | |
| | (0.014) | | | |
| $\text{miss}^{300m} \times \text{flood}^{+2}$ | 0.014 | | | |
| | (0.020) | | | |
| $\text{miss}^{300m} \times \text{flood}^{+3}$ | −0.033* | | | |
| | (0.019) | | | |
| $\text{miss}^{300m} \times \text{flood}^{+4}$ | 0.001 | | | |
| | (0.017) | | | |
| $\text{miss}^{400m} \times \text{flood}^{+1}$ | | −0.043*** | | |
| | | (0.014) | | |
| $\text{miss}^{400m} \times \text{flood}^{+2}$ | | 0.010 | | |
| | | (0.013) | | |
| $\text{miss}^{400m} \times \text{flood}^{+3}$ | | −0.024 | | |
| | | (0.020) | | |
| $\text{miss}^{400m} \times \text{flood}^{+4}$ | | −0.014 | | |
| | | (0.014) | | |
| Lower $\text{miss}^{500m} \times \text{flood}^{+1}$ | | | −0.018 | |
| | | | (0.024) | |
| Lower $\text{miss}^{500m} \times \text{flood}^{+2}$ | | | −0.008 | |
| | | | (0.021) | |
| Lower $\text{miss}^{500m} \times \text{flood}^{+3}$ | | | −0.044*** | |
| | | | (0.016) | |
| Lower $\text{miss}^{500m} \times \text{flood}^{+4}$ | | | −0.014 | |
| | | | (0.022) | |
| Higher $\text{miss}^{500m} \times \text{flood}^{+1}$ | | | | −0.020 |
| | | | | (0.020) |
| Higher $\text{miss}^{500m} \times \text{flood}^{+2}$ | | | | 0.029** |
| | | | | (0.014) |
| Higher $\text{miss}^{500m} \times \text{flood}^{+3}$ | | | | 0.014 |
| | | | | (0.014) |
| Higher $\text{miss}^{500m} \times \text{flood}^{+4}$ | | | | 0.009 |
| | | | | (0.018) |
| *Constant* | 9.696*** | 9.305*** | 9.895*** | 9.852*** |
| | (1.573) | (1.702) | (1.898) | (1.906) |
| Weekday FE | ✓ | ✓ | ✓ | ✓ |
| Month-Year FE | ✓ | ✓ | ✓ | ✓ |
| Zip code × year FE | ✓ | ✓ | ✓ | ✓ |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Observations | 18,701 | 19,290 | 19,707 | 19,707 |

*Note:* Dependent variable is the Ln sqm. price. Results for a coefficient from estimation equation (9), standard errors in parentheses are clustered at the municipality level. We include a variable controlling for the 2014 referendum. The reference are the months -3 - 0 before and > 5 months after the flood. In each specification, we use a buffer excluding a radius of 300m. ***, ** and * denote statistical significance at the 1%, 5% and 10% level.