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**Article — Published Version**

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Review of Regional Research

**Provided in Cooperation with:**

Springer Nature

*Suggested Citation:* Häse, Sophie; Hirte, Georg (2023) : The impact of unexpected flood events and adaption measures on lot prices, Review of Regional Research, ISSN 1613-9836, Springer, Berlin, Heidelberg, Vol. 43, Iss. 1, pp. 29-68,  
<https://doi.org/10.1007/s10037-022-00177-y>

This Version is available at:

<https://hdl.handle.net/10419/309260>

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# The impact of unexpected flood events and adaption measures on lot prices

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Accepted: 21 December 2022 / Published online: 6 March 2023  
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**Abstract** Associated with climate change are the rising frequency, probability, and intensity of natural hazards, as stated by IPCC (2014). To contribute to the evaluation of climate change consequences, we study the impact of river floods caused by torrential rain periods, which are supposed to become and already are one of the major future challenges. Since subsequent flood and adaptation measures are usually interdependent, identifying causal effects is the main challenge. Therefore we investigate a sequence of river floods and subsequent adaption measures in a natural experiment setting. Our study area is the city of Dresden, Germany in the time period from 2000 until 2017. Remarkable in this setting is the exogeneity of the first flood event in 2002 that hit the city unexpectedly after 60 years without considerable flood events. We use a complete set of lot transactions from 2000 until 2017 to study the effect of these events on lot prices. The basis of our identification strategy is a Difference-in-Differences design in which we control for an unstable assignment to treatment and control group. Additionally we consider the heterogeneity of the treatment, which is caused by the varying intensity levels during a flood. It shows that flood risk is incorporated into lot prices only after awareness is risen due to a sudden flood event and that a higher expected intensity increases discounts. A long-term effect can be verified once we control for adaption, such as public protection measures.

**Keywords** Climate change · Difference-in-Differences · Hedonic prices · Flood hazard · Natural disasters · Real estate and housing

**JEL Classification** D12 · Q54 · R21

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## Die Auswirkungen von unerwarteten Hochwasserereignissen und Anpassungsmaßnahmen auf Grundstückspreise

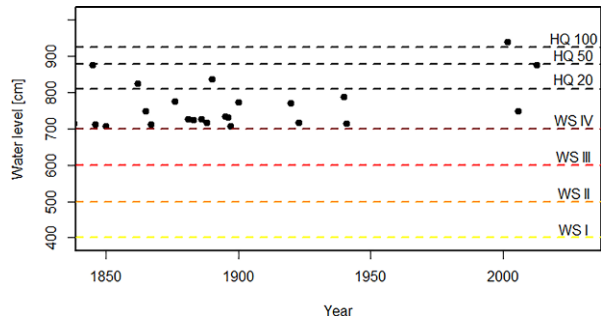
**Zusammenfassung** Naturkatastrophen in zunehmender Wahrscheinlichkeit, Häufigkeit und Intensität sind laut IPCC (2014) wesentliche Konsequenzen des Klimawandels. Mit unserer Untersuchung der Auswirkungen von Hochwasserereignissen an Flüssen leisten wir einen Beitrag zur Bewertung der Folgen des Klimawandels. Dabei fokussieren wir uns auf Hochwasserereignisse, die durch sintflutartige Regenperioden verursacht werden und zu einer der größten zukünftigen Herausforderungen zählen. Aufgrund der Abhängigkeit von Hochwasserereignissen und Flutschutzmaßnahmen ist die Identifikation kausaler Effekte nicht trivial. Im Rahmen eines natürlichen Experiments untersuchen wir eine Abfolge von Hochwasserereignissen und daraufhin geplanten sowie umgesetzten öffentlichen Flutschutzmaßnahmen. Unser Untersuchungsgebiet ist die Stadt Dresden in der Zeitperiode von 2000 bis 2017. Bemerkenswert in dieser Region ist die Exogenität des ersten betrachteten Hochwasserereignisses im Jahr 2002, welches die Stadt nach einer 60 Jahre andauernden Periode ohne nennenswerte Hochwasserereignisse vollkommen unerwartet traf. Unserer empirischen Untersuchung liegt ein vollständiger Datensatz von Grundstückstransaktionen der Jahre 2000 bis 2017 zugrunde. Mithilfe dessen untersuchen wir innerhalb eines hedonischen Preismodells die Auswirkungen dieser Ereignisse auf Grundstückspreise. Die Basis unserer Identifikationsstrategie ist ein Difference-in-Differences-Design. Innerhalb dessen kontrollieren wir für die sich im Zeitverlauf ändernde Definition von Treatment- und Kontrollgruppe. Zusätzlich berücksichtigen wir die horizontale Heterogenität des Treatments, welche sich durch verschiedene Überflutungsintensitäten äußert. Es zeigt sich, dass ein gegebenes Hochwasserrisiko sich erst dann in Grundstückspreisen niederschlägt, wenn ein Bewusstsein für dieses existierende Risiko durch ein plötzliches Hochwasserereignis geschaffen wird. Außerdem geht eine höhere erwartete Hochwasserintensität mit einem größeren Preisabschlag einher. Weiterhin können wir, unter Berücksichtigung öffentlicher Flutschutzmaßnahmen und wiederkehrenden Flutereignissen, einen langfristig andauernden Preisabschlag nachweisen.

**Schlüsselwörter** Klimawandel · Naturkatastrophen · Flutschutz · Überschwemmungsrisiko · Hedonische Preisanalyse · Differenz-von-Differenzen-Ansatz

### 1 Introduction

Associated with climate change is the rising frequency, probability, and intensity of natural hazards, as stated by IPCC (2014). To contribute to the evaluation of climate change consequences, we study the impact of river floods caused by torrential rain periods, which are supposed to become and already are one of the major future challenges. For this purpose we explore one potential consequence of climate change by exploring the impact of floods and flood risk as well as adaption measures on lot prices. In particular, we study an unexpected strong flood event, respectively, the

**Fig. 1** History of flood events in Dresden. Data: Schmidt (2000), Landeshauptstadt Dresden (2022b). Standard water level: 170 cm, WS: warning stage. (Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie 2019b)



suddenly revealed information on a stronger flood risk exposure, and address the impact of recurring floods and public protection measures.

The study area for our analysis is the city of Dresden that since 1845 experienced well-documented flood events, shown in Fig. 1. In the plot and in the analysis of this paper, we consider inundations exceeding the water level for the official current flood warning stage 4 for the city of Dresden, which corresponds to 400 cm (WS IV in Fig. 1)<sup>1</sup>. For consistency we refer to the common HQ<sup>2</sup> classification in the following. This classification considers the frequency in which flood events are expected to occur. A larger number indicates a less frequent event. For example, a flood event classified as HQ 10, is expected to occur once in 10 years and an HQ 50 event once in 50 years. The latter therefore is less frequent, but larger in extent. Hence, with respect to intensity, an HQ 50 event will cause greater damage to areas that are also flooded during an HQ 10 event, because of the higher water level in those areas.

Fig. 1 also reveals that although the city was hit by a considerable amount of floods since 1845, there were only three events recorded, that exceeded a water level of 700 cm since 1950. The first and most important event happened in 2002. It was considered an exceptionally strong flood event and hit the city unexpectedly. This flood in August 2002 was later called the hundred-year flood and had a peak water level of 940 cm. Hence, it exceeded the standard water level in the city area, which is 170 cm, by 770 cm. With respect to the HQ classification, this flood was later considered an HQ 100 event.<sup>3</sup> A second major flood happened in 2013 and, with a water level of 876 cm, was considered an HQ 50 event. The third flood was a minor event, classified as HQ 10, and happened in 2006.

However, already in the aftermath of the 2002 flood, the city began planning and constructing three large public protection measures. The timeline in Fig. 2 shows the chronology of events that are related to inundations and flood risk management. This case is interesting because it features several characteristics that may be typical

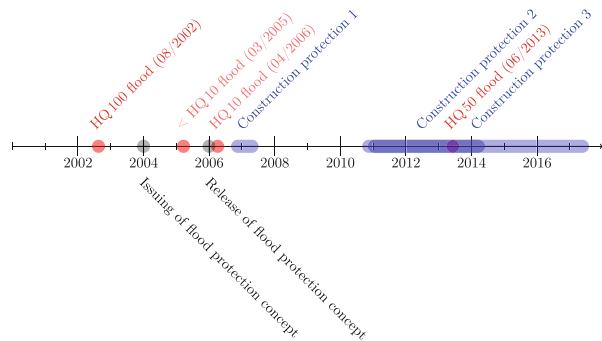
<sup>1</sup> With regard to the HQ classification a flood with a water level of 400 cm would be considered an HQ 5 event.

<sup>2</sup> In reference to Becker et al (2019), abbreviation HQT stands for the flood peak flow (HQ), measured in cubic meters per second, and T indicates the annuality.

<sup>3</sup> The HQ 100 zone has been defined according to area flooded in 2002 and reconfigured twice subsequently after protection measures have been constructed.



**Fig. 2** Timeline of flood events and adaption measures



under climate change. There is a first, unexpected strong flood that raises awareness of the flood risk. Subsequently, adaptation measures are implemented and further flood events occur. While one may expect that subsequent flood events are stretched over a longer time period, the short time between the flood events in Dresden makes it suitable to be used in an empirical study. In a natural experiment setting, we investigate this sequence of river floods and adaption measures that affected the city of Dresden, Germany, from 2002 until 2017. For that purpose, we apply a Difference-in-Difference (DiD) design to identify the causal impact of flood risk on lot prices. In our analysis, lot prices describe transaction prices for developed parcels of land.<sup>4</sup>

It is crucial to control for protection measures in a natural experiment setting, as adaption causes heterogeneity of the treatment group over time. We further distinguish multiple post-treatment periods to explore the immediate effect of the shock and study whether this price response is declining over time. In a robustness analysis, we also consider the spatial heterogeneity of the treatment by including information on flood intensity. We find that there is a large and highly significant price discount after the 2013 flood for lots that are not protected against HQ 100 floods and will not be protected in the future. Also, we provide evidence that there is a price discount immediately after the 2002 flood for parcels of land located in the high intensity zone while there is hardly any for those with low-risk intensity.

Our paper contributes to the literature in three ways: To our knowledge, it is the first study that examines an unexpected flood event at a river and controls for public intervention in the aftermath of the event. Second, it is the first study that considers subsequent flood events intertwined with adaptation measures. Third, we are the first to study heterogeneity of the treatment by considering intensity levels.

The rest of the paper is structured as follows. First, in Sect. 2, we give a short overview of the literature that covers the impact of flood events on real estate prices. We focus particularly on literature that concerns river floods and such that investigate our study area. Sect. 3 explains the theoretical impact of risk on property prices, the specification of the hedonic price function as well as the Difference-in-Differences method, and the integration of spatial dependence. It is followed by Sect. 4, where we describe our data and provide detailed information on HQ maps which serve as the basis for the definition of the treatment and control groups. The

<sup>4</sup> A detailed description of the properties included is provided in Sect. 4.

subsequent Sect. 5 explains our identification strategy. We explicitly discuss how the assumptions of the DiD approach can be fulfilled and the related construction of our treatment group and control group. The estimation results are explained in Sect. 6. We discuss critical issues and test our results for robustness in Sect. 7. The last part concludes our findings.

## 2 Literature review

Flood events occur for various reasons and have been challenging cities and regions for centuries. Depending on their location of interest studies deal with hurricanes, typhoons, and – as this paper – river floods caused by heavy rainfalls. The estimated effects on real estate prices vary over the cause of the flood and the location observed. In the following, primarily publications that use the hedonic price method to estimate impacts of flood events are discussed.<sup>5</sup> Also we explicitly consider literature that covers our study area.

A variety of studies investigates the impact of hurricanes on real estate prices in the USA, i.e. Bin and Landry (2013), Bin et al (2008), Bin and Polasky (2004), Speyrer and Ragas (1991) or McKenzie and Levendis (2010). Also, there are analyses of the impact of typhoons on housing prices in East Asia, i.e. Murakami and Seya (2019). River floods are the main focus of studies on European regions such as Votsis and Perrels (2016) and Daniel et al (2009). Atreya et al (2013), Shultz and Fridgen (2001) and Zhang (2016) deal with river floods in the USA.

The estimates for the discount on real estate prices caused by floods or flood risk thereby show a larger variance for river floods (8% to 44%) than for hurricanes (5% to 9%). A crucial finding of the literature is the effect of a vanishing discount over time. In Bin and Landry (2013) it is detected after 5 to 6 years. Zhang (2016) already finds a disappearing of the discount 2 years after the studied flood event. Votsis and Perrels (2016) explicitly investigate the disclosure of flood risk information, i.e. published risk maps and its impact on prices rather than actual events.

Also, the area of interest in this paper, which is the city of Dresden, has been the focus of previous papers. Kropp (2016) studies the impact of flood events on undeveloped land using data from Dresden and Meißen in Saxony as well as data from Rhineland-Palatinate and Saxony-Anhalt. Within the area of Dresden and for the period from 2002 to 2014 the final dataset comprises 2.677 transactions of which 169 are located in the HQ100 area. Kropp (2016) finds an expected discount on transaction prices for undeveloped land of 7% and on the standard land value of 6% compared to similar land areas without flood risk. However, no causal approach is used to investigate the effect of flood risk as only the pure information on location is utilized, not taking into account the awareness of flood risk and without any observations before the 2002 flood.

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<sup>5</sup> Some papers also aim to quantify the willingness to pay for hazard risk reduction from floods through the application of choice experiments, i.e. Botzen and van den Bergh (2012); Botzen et al (2013); Fuks and Chatterjee (2008). This however is not covered in this short review.

Kreibich and Thieken (2009) examine the case of the 2002 flood event (as well as the small flood events in March 2005 and April 2006) in Dresden. From expert and household interviews, they conclude that before 2002 neither households nor the local authorities have been properly prepared against floods due to faded risk awareness. This proves to be an important finding for our study as it provides evidence the exogeneity of the 2002 flood event.

In a rather recent paper, Pommeranz and Steininger (2020) study the 2013 flood event and investigate the impacts of spatial spillovers of flood risk on offering prices of houses and condominiums. The authors use a data set from the period of 2008 to 2016, which comprises 6,371 observations of asking prices for houses and 12,358 for condominiums. To identify flood zones they use the insurance-based ZÜRS system of hazard zones which is itself mainly based on hazard zones defined by the local authorities.<sup>6</sup> The authors find that there are indirect price effects which sum up to a 6.5% decline in prices for houses and a 4.8% decline in asking prices for condominiums. However, one may argue that the 2013 treatment is not exogenous as various protection measures have been installed between 2002 and 2013 in expectancy of a future flood event, so that a pre-treatment effect cannot be ruled out completely.

As is shown, due to data limitations and a lack of actual exogeneity of the investigated river flood event, the impact of unexpected river floods and protection measures on real estate transaction prices to our knowledge has not been studied by now. We, therefore, contribute to research by especially investigating the 2002 flood event as an actually exogenous shock with transaction data. This data is unbiased by expectations and covers the crucial period around 2002.<sup>7</sup> Also to the best of our knowledge adaption measures and heterogeneity of the treatment have not been explicitly considered by now.

### 3 Method

In the following, we provide a short overview of the applied methods in our study. First, we explain the theoretical impact of risk on real estate prices. Next, we specify the hedonic price function. Further, we discuss the extension of our function in the Difference-in-Differences framework and explain how we consider the spatial character of our data.

<sup>6</sup> What is called ZÜRS GK 4 would equal the HQ 10 zone and is only insurable for very high premium and not insurable at all. Also, the ZÜRS GK 3 which corresponds to the HQ 50 area minus the HQ 10 zone is not insured by all companies. Completely insurable and not as costly are the ZÜRS GK 2 and GK 1 zones. The former comprises the HQ 200 minus the HQ 50 area. The ZÜRS GK 1 refers to areas that are flooded less than every 200 years.

<sup>7</sup> Pommeranz and Steininger (2020) state that their set of asking prices mainly equals transaction prices, finding only a small – and probably not significant – deviation of the mean asking price from the mean transaction price in 2015.

### 3.1 Theoretical impact of risk on real estate prices

Economics of risk suggests an adverse effect of risk on utility for risk averse individuals. Hence, we expect a negative impact of flood risk on housing prices, as the latter can be regarded a measure of utility.

However, there might also be an impact not only of actual risk, but also of perceived risk, as pointed out by Aldy and Kip Viscusi (2014). The authors illustrate how a decrease in utility might occur, even for individuals that do not face actual risk, simply because of perception. In our case, this would mean areas outside of the HQ 100 area might face a discount in transaction prices.

Various factors can influence the risk perception. First, the presence of the river itself can influence perceived risk. Second, the information on previous flood events in the city, in the media, or personal experiences can change the perception of flood risk. Third, the adaption measures themselves might influence the perception of risk. Dams, or polders are constantly visible. Mobile protection measures might be less present in everyday life. However, at least in the case of our study area, there are regular test runs of the mobile protection walls, that are even announced in the media (see e.g. Sachsen Fernsehen (2021)). Hence, the difference between the protection measure types might be less pronounced.

We cannot measure the actual impact of perceived risk in this study. The impact of distance to the river Elbe captures not only perceived risks but also the amenity of the river. Data on media and personal experience would be too vague. The type of adaption measure – although the best proxy for perceived risk in our case – can also not be used due to the limited number of observations for lots protected by each measure as well as due to the strong spatial clustering of the observations protected by each measure. The mobile protection wall is only implemented in the city center, where space is limited and prices are generally higher. Dams are installed in the outskirts, where prices for housing are commonly lower. Hence, the investigation of the effect of perceived flood risk on housing prices remains an interesting question for further research.

In our analysis we therefore stick to the consideration of actual risk represented by the HQ 100 maps.

### 3.2 Specification of the hedonic price function

The price  $P_i$  of a developed parcel of land  $i$  is, in reference to Rosen (1974), represented as a linear combination of the quantities of its attributes weighted by their implicit prices, one of which is the risk of flooding, as given by Eq. (1).<sup>8</sup>

$$P_i = f(X_i, Z_i, H_i) \quad (1)$$

<sup>8</sup> To capitalize the effect of flood risk exposure correctly, we assume inelastic housing supply. On average, there was an increase in the housing stock of 62 houses and 9,490 apartments. In the meantime, the population grew by 55,176 from 2000 to 2017, and the total number of households by 58,561. This indicates that the supply might not be perfectly inelastic but rather inelastic and faces an increasing demand (Landeshauptstadt Dresden 2017a, 2018).

In our analysis,  $X_i$  represents the vector of lot<sup>9</sup> and house-specific attributes such as lot size, living space, or the number of floors. Vector  $Z_i$  comprises local amenities and environmental attributes such as the distance to the river, noise, or the distance to public transportation. The location within the hazard zone HQ 100, and hence the flood risk, is represented by  $H_i$ .<sup>10</sup>

Since the distribution of lot prices is strongly right-skewed, we estimate the conditional mean of log prices. Hence, the baseline hedonic price function is given by Eq. (2).

$$\log P_i = \beta X_i + \theta Z_i + \varsigma H_i + \epsilon_i, \quad (2)$$

Here  $\beta$ ,  $\theta$  and  $\varsigma$  are the vectors of coefficients and  $\epsilon_i$  is an i.i.d. error term. To control for general price changes in the housing sector, we adjust the lot prices according to the housing and building price index (Statistisches Bundesamt 2020). A general price dampening effect of the flood event would therefore be omitted.

### 3.3 Spatial dependence

The majority of studies that investigate the impact of flood events on housing prices controls for environmental and spatial amenities as well as spatial dependence to avoid omitted variable bias and spatial autocorrelation. However, whereas there is a broad consensus on the choice of explanatory variables, the assumed origin of spatial dependence differs throughout the literature. Bin et al (2008) use a spatial error model (SEM) whereas Bin and Landry (2013) and Zhang (2016) choose a spatial lag model. Atreya et al (2013) decide on a combined spatial lag and spatial error model, Votsis and Perrels (2016) apply a Spatial Durbin model while Pommeranz and Steininger (2016, 2020) implement a Spatial Durbin Error model (SDEM).<sup>11</sup> Investigating heterogeneity over the distribution of sales prices, Murakami and Seya (2019) use a spatial filtering approach to control for spatial dependence within their analysis.

We decide on an SEM to capture small scale and unobserved neighborhood related effects. The corresponding econometric specification is represented by Eq. (3).

$$\begin{aligned} \log P_i &= \beta X_i + \theta Z_i + \sum_{\phi} \varsigma H_i + u_i \\ u_i &= \lambda W u_j + \epsilon_i \end{aligned} \quad (3)$$

<sup>9</sup> In our analysis, lot prices describe transaction prices for developed parcels of land. A detailed description of the properties included is provided in Sect. 4.

<sup>10</sup> The specific attributes in each category which we consider in the analysis are discussed in detail in Sect. 4.

<sup>11</sup> The vast majority of the literature only reports and interprets direct effects whereas Pommeranz and Steininger (2020) conclude from their results that spatial spillovers exist and that it's mainly the indirect effect that drives discounts in housing prices.

To generate our spatial weights matrix ( $W$ ) we define lots within a 300 m euclidean distance as neighbors. The cutoff distance ensures a sample size large enough to be evaluable even when lots without any neighbors are excluded. Also the distance is chosen small enough to explicitly control for small-scale neighborhood effects. The matrix is row standardized and within the 300m all neighbors are weighted equally.<sup>12</sup>

However, to address the issue of potential spillover effects as found in Pommeranz and Steininger (2020), we also estimate an SDEM, which we report in our robustness section.

We dismiss the spatial lag model, as controlling for spatial dependence in this way might interfere with the effect of flood risk on lot prices because affected lots are naturally neighboring.

There is another type of potential spatial dependence that we cannot control for. Suppose people move from the treatment to the control area in the aftermath of the flood events in such numbers that this increases lot prices in the control group. In this case, we overestimate the lot price effect of the flood event in the treatment area. Unfortunately, we cannot observe the movements with the data at our disposal. However, we presume that most people who move out from the HQ 100 area are risk-averse and are unwilling to move to the neighboring area that is also prone to flood risk. Hence, we consider it rather unlikely that this kind of spatial dependence exists between the treatment and control groups. Nonetheless, this remains a limitation of our paper.

### 3.4 Difference-in-Differences Design

To make use of the natural experiment character of the setting, we apply a DiD design that enables us to quantify causal effects of flooding and flood risk on lot prices. The exogeneity of the sudden flood event in 2002, that has not been foreseen or presumed neither by the local authorities nor the inhabitants, suggests this type of approach. Whether we can interpret the outcome as a causal effect depends on the exogeneity of the treatment and a stable treatment as the main identifying assumptions as well as on the properties of the treatment and control group. We thoroughly discuss the DiD assumptions in Sect. 5, where we also explain our general strategy as well as the construction of the treatment and control groups.

## 4 Data description

In the following, the data used in the study is explained. Summary statistics of the variables, which enter the estimation on a metric scale in the analysis, are given in Table 7 in the Appendix. Table 8 in the Appendix, covers all nominal and ordinal scaled variables and reports their categories as well as the corresponding total number and share in the sample.

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<sup>12</sup> To ensure robustness with regard to the spatial weights matrix, we repeated the analysis for a distance of 500 m (see Sect. 7).

## 4.1 Lot and house characteristics

Our dataset comprises information extracted from transaction contracts from 2000 until 2017. As this data is provided by Landeshauptstadt Dresden, Amt für Geodaten und Kataster (2018), we have the full set of transactions for this period at our disposal. It includes developed lots with single-family houses, multi-family houses as well as commercial buildings, and undeveloped land. Due to the small number of transactions in that category, undeveloped land is excluded in our study.

The transaction contract database contains information on the lot price which has been paid, several lot- and house-specific features as well as contract attributes. Lot and house-specific attributes comprise the total space of the lot as well as the living space of the house and the number of floors. The type of the house can be divided into the categories single-family house, multi-family house and commercial buildings and is further specified by structural features that indicate whether it is e.g. a villa (large and rather luxurious, detached, one- or multi-family house), row-end house, or semi-detached house. Additionally, there is information on the condition of the house, year of construction and whether it is rented. The contract-specific information we use is the type of seller or more specifically whether buyer and seller are related. The date of the contract reveals the year of transaction, which we use to control for overall time effects.

## 4.2 Environmental features

As all observations are geo-coded, we merge information on spatial amenities using GIS to include price-defining attributes that are not given in the contracts to capture various influences of location. We add information on street and rail noise<sup>13</sup> as traffic noise is generally thought of as a crucial price defining factor.<sup>14</sup> Furthermore, information on public transport accessibility is included by using the distance to light rail stations.<sup>15</sup> A negative correlation between noise exposure and public transport accessibility is obvious but within this analysis unproblematic. The same is true for the distance to the motorway. Checking for multicollinearity using variance inflation factors (VIF), the variables of interest are unaffected by any multicollinearity. Though the proximity to water is correlated with the feature of interest which is the location within the flood risk hazard zone, we include distance to the main river Elbe. The importance to include the proximity or distance to the river is pointed out in Bin et al (2008).<sup>16</sup> Further, time invariant location related aspects are controlled for by the inclusion of the ZIP code. Those spatial fixed effects also capture the

<sup>13</sup> Information on rail noise is obtained from Eisenbahnbundesamt (2017) and street noise data from Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie (2017).

<sup>14</sup> See e.g. the meta-analysis of Kopsch (2016).

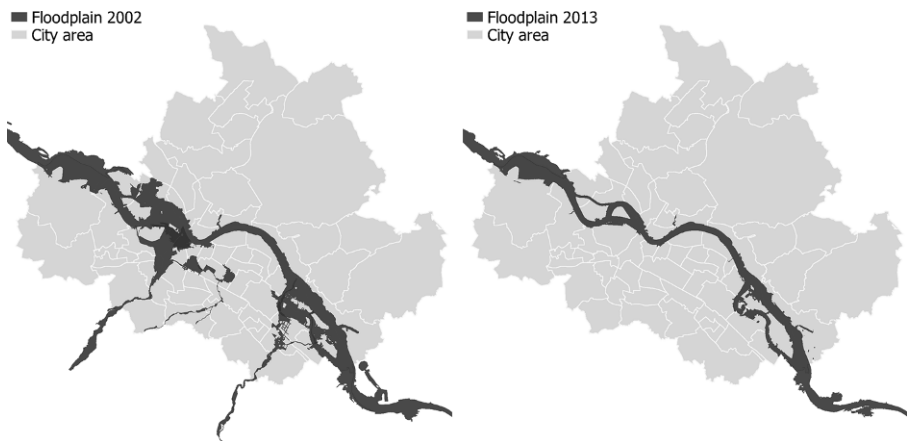
<sup>15</sup> Light rail can be considered the most widely used public transport mode in the city of Dresden. The effect of public transport accessibility on real estate prices is studied e.g. by Cordera et al (2018) and Dubé et al (2014).

<sup>16</sup> Also Rouwendal et al (2014) study explicitly the value of proximity to water and find an increase in price by 5%.

distance to the city center. Last but not least we include information on the altitude of the lot in relation to the river Elbe.<sup>17</sup> This information helps us to identify comparable lots with regard to flood risk.

### 4.3 Floodplains and hazard zones

As our variable of interest and proxy for flood risk we use the HQ 100 hazard zone. It has been created after the 2002 flood event, which is why the actual flood plain and this first version of the HQ 100 area are mostly identical. The floodplains of the 2002 and 2013 flood events are displayed in Fig. 3. Hazard zones are based on geodetic models and defined in the flood protection concept of the State Reservoir Administration of Saxony.<sup>18</sup> They indicate in which interval floods occur in a specific area. Hence, a lot located in the HQ 100 area is expected to be flooded once every 100 years.<sup>19</sup> Further, the HQ 100 hazard zone consists of high-intensity, medium-intensity, and low-intensity areas. High intensity is described as an expected water level higher than 2 m, medium intensity below 2 m but above 0.5 m, and low intensity lower than 0.5 m.<sup>20</sup> The left map of Fig. 4 displays the extension of the HQ 100



**Fig. 3** Floodplains 2002 and 2013 and city districts. Data: Landeshauptstadt Dresden (2015, 2019b, 2022c)

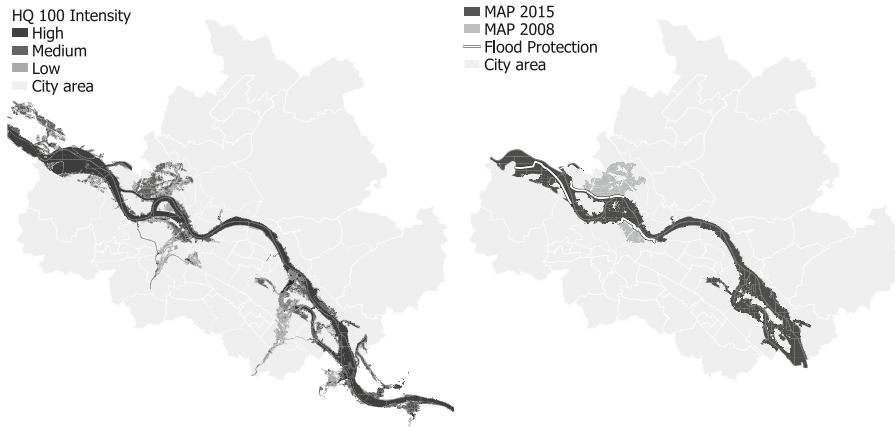
<sup>17</sup> Information on altitude are obtained from Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie (2017).

<sup>18</sup> ESRI shape-files of the hazard zones are conceptualized by HGN Hydrogeologie GmbH Ingenieurgesellschaft für Wasser Boden Umwelt (2006).

<sup>19</sup> Lots in the HQ 50 area are expected to be flooded every 50 and lots in the HQ 20 zone every 20 years.

<sup>20</sup> Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie (2019a) provide a verbal description of the hazard zones targeting the expected damage. Here high intensity means humans and animals also inside of buildings are highly endangered, significant damage and sudden destruction of buildings might occur. Medium intensity is described as humans and animals outside of buildings are highly endangered, inside of buildings are rarely endangered and property damages on buildings might occur. Low intensity is defined as humans and animals outside of buildings are rarely endangered and property damages on buildings (esp. basement) might occur.





**Fig. 4** Hazard zone HQ100 intensity levels and protection measures. Data: Landeshauptstadt Dresden (2019a, 2022c,a); Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie (2012)

hazard zone, and the respective intensity zones. As the high-intensity area during an HQ100 categorized flood will be in general located in the very proximity of the river, it is obvious that these areas are also more likely to be flooded by events which are smaller but much more common. Those are categorized as HQ20 or HQ50. However, not only hazard zones and intensity levels are crucial for our study.

Since the flood event that occurred in 2002, three large HQ100 protection measures have been installed in the city as displayed on the right in Fig. 4. According to Landeshauptstadt Dresden (2020) the first one, built between September 2006 and March 2007, is a mobile protection wall that guards the historical inner city against HQ100 flood events. The second protection measure consists of several dams that have been rebuilt or newly built between September 2010 and June 2014. It prevented areas north of the dam from damage during the 2013 flood. However, that was not the case for areas, which are nowadays protected by the third protection measure in the western part of the city. This third measure was built between November 2011 and August 2017 but was not finished to an extend where it would have prevented the flooding of this area in 2013.

There are updates of the original HQ100 zone available, provided by the Landeshauptstadt Dresden (2019c), which consider those flood protection measures. However, contrary to the original HQ100 zone we described above, those maps do not contain information on intensity and only cover the main river Elbe but no secondary rivers. Fig. 4 displays the extension of this HQ100 zone before the construction of protection (MAP2008) and after the construction of a mobile protection wall in the south and a dam in the north (MAP2015). The names of those maps suggest the year of release.

## 5 Identification Strategy

To estimate causal effects utilizing a DiD design, we have to meet certain assumptions regarding our sample, respectively regarding our treatment and control groups.

### 5.1 Assumptions regarding the DiD design

In the following the assumptions required by the DiD design, in reference to Lechner (2010) are discussed.

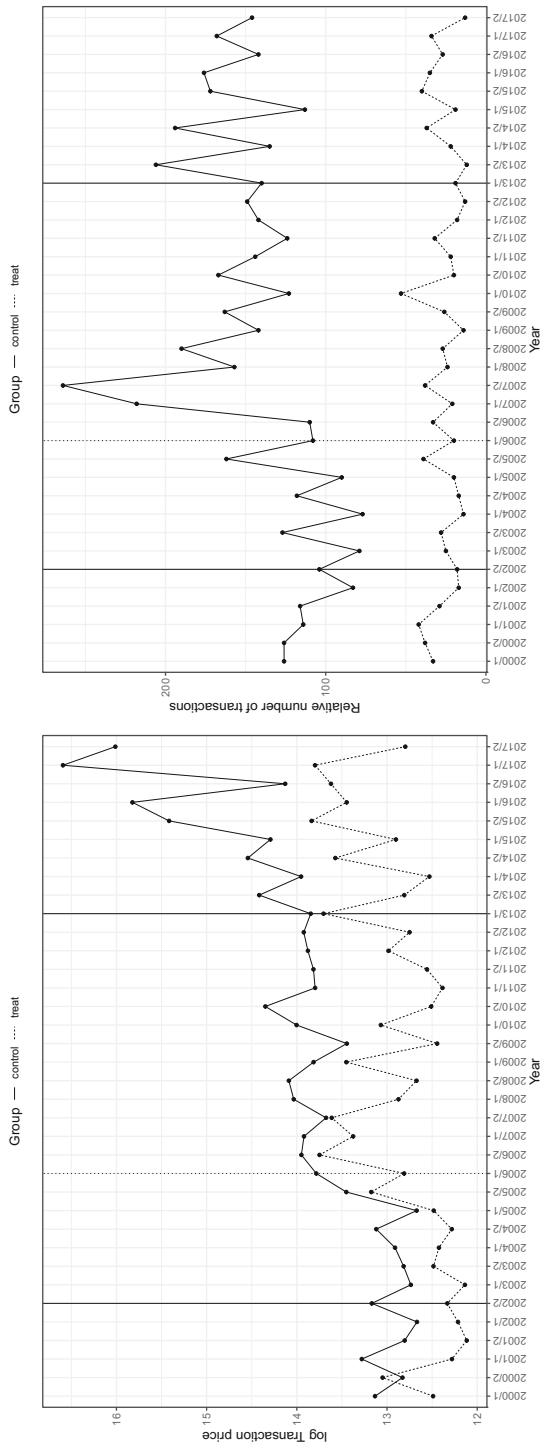
*No pre-treatment effect* Due to the 60 years flood free period prior to 2002, we can consider the flood event in 2002 to be unexpected and hence exogenous. The survey of Kreibich and Thieken (2009) confirms that local authorities, as well as the inhabitants of the city of Dresden, have neither been prepared nor were they conscious of the risk. Hence, we conclude that people on average did not act in expectation of a flood prior to 2002, implying that there is no pre-treatment effect.

*Stable Unit Treatment Value assumption* The assignment to the treatment and control group appears to be straightforward at first sight. Inspection of the map of the HQ 100 hazard zone shows a well-defined area that is expected to suffer from an HQ 100 flood event.

However, considering the before pictured timeline of events (see Fig. 2), it shows that a treatment group based on this initial HQ 100 map is not stable in a time-dimension, and might therefore not fulfill the stable unit treatment value assumption (SUTVA). The assignment to the treatment group in reference to the HQ 100 map which was published right after the 2002 flood, is not appropriate for later time periods when protection measures have already been installed. Therefore, to examine the effect of flood risk for periods after the installation of protective measures, we must construct the treatment group by considering those protection measures and hence, the over time spatially changing extend of the treated area. In addition, the question arises, whether we observe a spatially homogeneous treatment. Lots located closer to the river might be affected stronger than lots that are still inside the HQ 100 area but further away from the river. This aspect is investigated within our robustness section by utilizing the previously described intensity levels, that come with the initial HQ 100 map. Apart from that, a shift in demand from areas with flood risk exposure to those without cannot be observed as shown in Fig. 5. Hence, given we define the treatment group correctly considering protection, there are no omitted treatments.

*Exogeneity* The treatment shall be exogenous and must not have an effect on the covariates. Most explanatory variables in our approach will fulfill this condition by definition as they are invariant or simply not likely to be affected by the treatment. An exception might be the condition of the building. After a flood event, it is more likely for an object to be renovated in general or renovated earlier than it would have been without the treatment. Looking at the descriptive statistics we find 29.5% of the houses to be fully renovated in the treatment group whereas in the control group 36.2% are fully renovated.<sup>21</sup> The percentage of partly renovated and not renovated

<sup>21</sup> This difference is statistically significant at a  $p$ -value  $< 0.05$ .



**Fig. 5** *Left:* Biannual mean log transaction price by treatment group and control group. (Treatment area until 2006: MAP 2008; Treatment area from 2007: MAP 2015). *Right:* Biannual number of transactions by treatment group and control group. Data: Landeshauptstadt Dresden, Amt für Geodaten und Kataster (2018)

houses is about equal in both groups. For lots with no information on the condition, we find a slightly larger number in the treatment group with 26.9% than in the control group with 21.4%.<sup>22</sup> If the renovation status improves, the selling price of a real estate might experience a slight upward bias. Thus, we would observe a smaller price discount due to the flood than there actually would be if there was no effect of the treatment on restoration. Apart from the distorted magnitude, this bias does not negate the existence of the price discount. On account of these assumptions, we conclude that the 2002 flood event was an exogenous shock and makes the setting an excellent base for the analysis of a causal effect of a flood event using a DiD approach.

*Common trend* When discussing the common trend assumption in the case of our study, it must be considered that what we observe are repeated cross sections rather than panel data. Hence, this assumption cannot be tested as conveniently. Also, the pre-treatment period, where the trend should be parallel, is comparably short for our analysis. In conclusion, we can only discuss why or why not a common trend is reasonable to be assumed, supported by the following descriptive plots. The left panel of Fig. 5 shows the biannual trend of the mean log transaction price for the treatment and the control groups, while the right panel displays the biannual number of transactions of both groups. The two solid vertical lines illustrate the major flood events in 2002 and 2013. The dotted vertical line represents the minor flood event in 2006. Apparently, the pre-treatment periods do not reveal any difference in the trend between both groups. Concerning the post-treatment periods, it is crucial to consider the assignment to the treatment and control groups. From 2000 until 2006, we use MAP 2008 as proxy for the treated area. From 2007 on, protection measures were installed as described in Sect. 4.3. Hence, from 2007 until 2017 we use MAP 2015 as proxy for the treated area.<sup>23</sup> Further, it has to be considered, that in the plot, no additional defining factors are controlled for.

Theoretically, a reason the common trend assumption could be violated would be a grown or shrunk demand for lots and houses in the vicinity of water, esp. the river Elbe, that is independent of the flood risk and actual flooding. This is the only attribute connecting those areas apart from the flood risk itself.<sup>24</sup> We control for the proximity to the river Elbe to capture a potential trend to move towards the river or away from the river independently of the flood risk. Also, the graph on the right hand side in Fig. 5 shows the biannual number of transactions in the treatment and control group. At least for the pre-treatment period, there is no obviously different trend between both groups visible. For the post-treatment periods the same limitations apply as for the left hand side plot, so that we cannot interpret the trend in the period of 2007 to 2013.

<sup>22</sup> This difference is statistically significant at a  $p$ -value  $< 0.05$ .

<sup>23</sup> The construction of the treatment group as well as mentioned limitations arising in this regard are further discussed in Sect. 5.2.

<sup>24</sup> A changed land development plan that might prohibit the construction of new buildings in the HQ 100 zone might have an effect on the supply of housing in the treated area, but still would be associated with the flood risk and hence a result of the treatment.

Apart from that, there is no obvious reason why the treated area should have had a different trend except for the treatment.

*Common support assumption / Comparability of observations* Eventually, the control group and the treatment group must be comparable. The treatment group of the analysis comprises all lots that are located within the HQ 100 hazard zone.<sup>25</sup> Concerning the control group, all lots outside this hazard zone are the obvious candidates for being included in the control group. However, looking at the summary of descriptive statistics of lots and houses inside and outside the hazard zone several structural differences are revealed. Especially the outer districts of the city in the north and south had been smaller villages that have been incorporated into the city of Dresden. This yields different house types with mostly larger space and a smaller number of floors. Also, amenities in those suburbs differ significantly. Last but not least there is no potential flood risk at all for the higher elevated regions in the north and the south of the city. With respect to this, we restrict the control sample. Since our aim is to explore especially the potential flood risk and properties in the control and treatment group have to be comparable, we use the difference in altitude relative to the river Elbe as the criterion to define the control group. We decide to choose a threshold of 12.5 m, i.e. all lots more than 12.5 m above the Elbe level are excluded from our sample.<sup>26</sup>

To summarize this discussion: most of the central assumptions of the DiD design are generally fulfilled. To prevent a bias caused by the violation of the stable unit treatment value assumption, we control for this unstable treatment area by considering the adjusted HQ 100 maps in constructing our treatment group. This is explained in detail in the following section. So that finally, it allows us to interpret our empirical results as causal effects of flooding on lot prices.

## 5.2 Construction of the treatment group

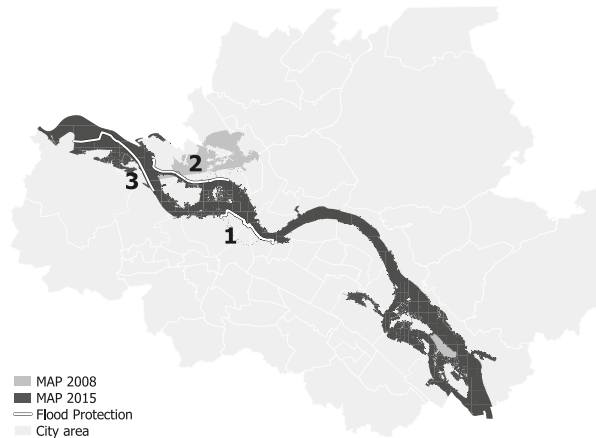
To meet the stable unit treatment value assumption, we have to carefully consider the sequence of inundation related events and measures. The public HQ 100 protection measures are shown in Fig. 6. Notably, areas affected by an HQ 100 flood changed over time.

The first protection measure (displayed as ‘1’ in Fig. 6), a mobile protection wall to cover the inner historic city, was in construction from September 2006 and was finished in March 2007, hence, already functioning during the flood event in 2013. The second one (displayed as ‘2’ in Fig. 6) combines multiple (re)constructed dams, built between September 2010 and June 2014. It prevented the areas north of the dam from damage during the 2013 flood. The third protection measure (displayed as ‘3’ in Fig. 6) in the western part of the city was built between November 2011 and

<sup>25</sup> Though this zone has been defined in 2004 it is configured according to the flood levels of 2002. We use this definition instead of the actual flooding because it already includes three intensity levels of the flood risk experts have derived from actual flooding levels.

<sup>26</sup> The cutoff value 12.5 m is chosen, so that the sample remains large enough for evaluation, but excludes possibly flooded areas from secondary rivers, as no data that considers protection on those is available.

**Fig. 6** Protection measures: (1) Inner-city wall, (2) Northwestern dam, (3) Southwestern dam. MAP2008 comprises also the dark gray areas of MAP2015. The medium gray areas of MAP2008 are exclusively to this map. Data: Landeshauptstadt Dresden (2019a, 2022c,a)



August 2017 and was not finished to a point where it could have prevented flooding of the south-western area in 2013.

In conclusion the treatment group is constructed as follows. In general we simply define the areas which are exposed to HQ 100 categorized flood risk as the treatment group and the lots that are not exposed but within a 12.5 m difference in altitude relative to the river as the control group. To identify the exposed areas, we utilize 3 different HQ 100 risk maps to capture the protection induced change of the exposed areas. We distinguish the following periods:

- Pre Reference / Pre-treatment period (00–02).
- Post1 First post-treatment period (02–06): No protection. MAP2008 applies.
- Post2 Second post-treatment period (07–13): Functioning protection measure ‘1’, not yet functioning measure ‘2’. None of the available maps apply.
- Post3 Third post-treatment period (13–17): Functioning protection measures ‘1’ and ‘2’. MAP2015 applies.

From 2007 to 2013 non of the available maps applies and hence non of the maps properly approximate the treatment area in that period. The technical description of this period in the list below is therefore highlighted in gray. Subsequently the dummy variable indicating the treatment group  $H_i$  is constructed as follows:

$$H_i = \begin{cases} 0, & \text{if Year} = 2000\text{--}2002 \text{ \& } \text{MAP 2008} = 0 \\ 1, & \text{if Year} = 2000\text{--}2002 \text{ \& } \text{MAP 2008} = 1 \\ 0, & \text{if Year} = 2002\text{--}2006 \text{ \& } \text{MAP 2008} = 0 \\ 1, & \text{if Year} = 2002\text{--}2006 \text{ \& } \text{MAP 2008} = 1 \\ 0, & \text{if Year} = 2007\text{--}2013 \text{ \& } \text{MAP 2015} = 0 \\ 1, & \text{if Year} = 2007\text{--}2013 \text{ \& } \text{MAP 2015} = 1 \\ 0, & \text{if Year} = 2013\text{--}2017 \text{ \& } \text{MAP 2015} = 0 \\ 1, & \text{if Year} = 2013\text{--}2017 \text{ \& } \text{MAP 2015} = 1 \end{cases} \quad (4)$$

The time of the treatment is the flood event in 2002 but we distinguish the 3 above mentioned post-treatment periods. This is captured by the binary variable

$K_i^\tau$ . It indicates whether the lot is sold after a certain point in time with  $\tau \in (\text{Post1}, \text{Post2}, \text{Post3})$ .

Hence, the DiD dummy is constructed as:

$$DiD_i^{\text{post1}} = \begin{cases} 0, & \text{if Period} = \text{Pre} \ \& \ H_i = 0 \\ 1, & \text{if Period} = \text{Post1} \ \& \ H_i = 1 \end{cases} \quad (5)$$

$$DiD_i^{\text{post2}} = \begin{cases} 0, & \text{if Period} = \text{Pre} \ \& \ H_i = 0 \\ 1, & \text{if Period} = \text{Post2} \ \& \ H_i = 1 \end{cases} \quad (6)$$

$$DiD_i^{\text{post3}} = \begin{cases} 0, & \text{if Period} = \text{Pre} \ \& \ H_i = 0 \\ 1, & \text{if Period} = \text{Post3} \ \& \ H_i = 1 \end{cases} \quad (7)$$

Also the parameter  $DiD_i^{\text{post2}}$  for the post-treatment period between 2007 and 2013 cannot be interpreted due to the non-availability of the according HQ 100 map and is therefore highlighted in gray. For this period the SUTVA is violated and the DiD parameter is biased. If we used MAP 2008 as proxy, lots that are already protected would be part of the treatment group. If we used MAP 2015, lots that actually are treated would be part of the control group. As we technically have to choose an area for this second post-treatment period, we decided on MAP 2015.

In conclusion, this yields the following regression model for our main analysis, represented by Eq. (8). With  $K_i^\tau$  being the indicator of the period and  $\tau \in (\text{Post1}, \text{Post2}, \text{Post3})$ ,  $H_i$  capturing the treatment group constructed as shown in Eq. (4) and the corresponding DiD terms, represented by the interaction of  $K_i$  and  $H_i$ .

$$\log P_i = \beta X_i + \theta Z_i + \zeta H_i + \sum_{\tau} \vartheta^{\tau} K_i^{\tau} + \sum_{\tau} \omega^{\tau} \overbrace{(H_i \cdot K_i^{\tau})}^{DiD_i^{\tau}} + u_i \quad (8)$$

$$u_i = \lambda W u_j + \epsilon_i$$

**Hypotheses** We expect to find a price discount right after the 2002 flood event (in the first post-treatment period) for lots exposed to flood risk. In the second post-treatment period, the DiD parameter is expected to be smaller if not insignificant at all, due to the instability of the treatment group caused by the implemented protection measures. For the third post-treatment period, expectations are not as clear. On the one hand, the discount on prices for lots exposed to flood risk might be smaller compared to the first post-treatment period, due to the forgetting effect as described in Bin and Landry (2013) and Zhang (2016). On the other hand, the discount might be larger than in the first post-treatment period, due to the recurring flood event in 2013.

## 6 Results

The regression results of our main analysis are depicted in Table 1. In this DiD regression, we control for spatial dependence estimating an SEM and include spatial

**Table 1** Main results

Dependent variable: $\log(\text{Price})$		
SEM		
Treat	-0.006 (0.046)	
Post1	-0.099*** (0.025)	
Post2	0.002 (0.024)	
Post3	0.279*** (0.027)	
$DiD_{\text{post1}}$	-0.092* (0.055)	
$DiD_{\text{post2}}$	-0.038 (0.052)	
$DiD_{\text{post3}}$	-0.198*** (0.055)	
Controls	Yes	
Lambda	0.706	
Observations	Treatment	Control
N00-02	157	552
N02-06	216	988
N07-13	339	2294
N13-17	227	1281
BIC	8458.263	
AIC	8122.839	
LR Test (df = 1)	700.236***	

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

fixed effects in the form of ZIP codes.<sup>27</sup> In the following, we will focus especially on the interpretation and discussion of the DiD parameters. As pointed out in Sect. 5.2, not all of the DiD parameters can be interpreted.

*Post-treatment period 1* The DiD parameter for the first post-treatment period is given by ( $DiD_{\text{post1}}$ ) in Table 1. This post-treatment period starts in 2002, after the flood event and ends in 2006, before the first public protection measures have been installed. The parameter can be interpreted, as the available HQ map (MAP2008) and the extend of protected areas in this period align. It reveals a negative effect to a significance level of  $\leq 10\%$ . Hence, lots located in the HQ100 exposed area, show a discount of 9.2% in the mean. The rather small significance level may be due to several reasons. First, the investigation does not distinguish between different intensity levels. Less intense affected areas might show a smaller discount than more

<sup>27</sup> The table covers only the variables of interest. Full regression results are provided in Table 9 in the Appendix. In addition the baseline OLS regression without consideration of spatial dependence is reported in Table 10 in the Appendix and juxtaposed with the results of the main SEM regression.



severe affected areas. This issue is tackled and explained in further detail in Sect. 7. Second, even before the construction of protection measures, the implementation of such has been discussed publicly, which might have caused an anticipation effect in the later years of the first post-treatment period.

*Post-treatment period 2* For the second post-treatment period, which ranges from 2007 to 2013, no interpretation is acceptable. In the analysis, MAP2015 is used as proxy for the treated area. However, this map does not align with the actual state of protection at this point in time<sup>28</sup> which causes lots that were actually still at risk in this period, to be incorrectly assigned to the control group. Hence, the SUTVA does not hold for this period. Given this violation of the assumption, the insignificance of the corresponding parameter ( $DiD_{post2}$ ) is to be expected. In this regard it is important to mention that the insignificance does not verify the absence of a discount in this period, but is solely a shortcoming of the model. We simply cannot make a statement about the existence or magnitude of a discount in the second post-treatment period based on our model.

*Post-treatment period 3* In the third post-treatment period, MAP2015 is used, which aligns to the state of protection at this point in time. As shown in Sect. 4.3, this map covers the two public protection measures, which had been implemented by then. Hence, the DiD parameter for this period ( $DiD_{post3}$ ) can be interpreted. It reveals a significantly negative effect to the 1% significance level for lots located within the HQ 100 area. Compared to the first post-treatment period, the parameter is even larger in magnitude and has a higher significance. In the mean, the discount amounts to 19.8%. This parameter ( $DiD_{post3}$ ) might be larger than it was for the first post-treatment period ( $DiD_{post1}$ ) due to several reasons. First, a majority of lots still exposed to HQ 100 flood risk, cannot expect to be protected in the future, as it is simply technically not possible. Second, lots still exposed to HQ 100 flood risk, are presumably located closer to the river and hence face a higher flood intensity, which might increase the discount. And third, as the timeline (see Fig. 2) reveals, the second major flood event happened in 2013, which may have increased the awareness of flood risk again and therefore extend the discount on exposed lots sold in the aftermath of the 2013 flood.<sup>29</sup>

Additionally, according to our results, we cannot explicitly confirm nor deny the findings of Bin and Landry (2013) and Zhang (2016), who find diminishing effects of flood risk on housing prices over time. The reason for this is the limited comparability of the case studies.

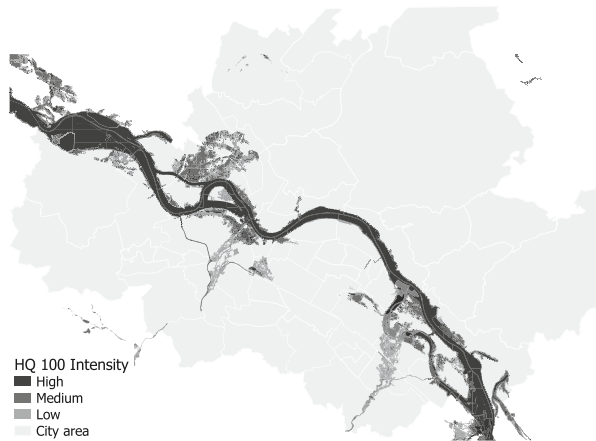
## 7 Discussion and robustness

In the following, we check our results for robustness by investigating the relevance of intensity levels, extending the sample and shifting the date of the shock to examine whether the actual event or the disclosure of risk maps is the actual treatment. We

<sup>28</sup> There is no map available that matches this period, as maps are not frequently updated.

<sup>29</sup> Unfortunately, we cannot examine the single effect of the 2013 flood event, as it also falls together with the completion of the third protection measure.

**Fig. 7** HQ 100 Intensity levels.  
Data: Landeshauptstadt Dresden  
(2022c); Sächsisches Landesamt  
für Umwelt, Landwirtschaft und  
Geologie (2012)



also relax the assumption of a 500m distance defining the neighbors in our spatial weights matrix and check for spatial spillover effects.

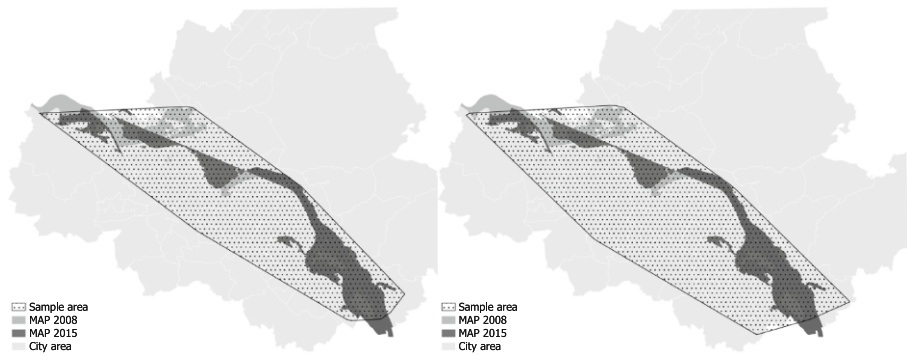
## 7.1 Heterogeneity in intensity

As mentioned in Sect. 4.3, the HQ100 map released in 2004 consists of three intensity levels (see Fig. 8). The high-intensity area for an HQ100 event is mainly the area closest to the river. It further graduates to medium intensity and finally, low intensity as the distance to the river increases.<sup>30</sup> We use these intensity levels to investigate the flood as a heterogeneous treatment. Referring to the definition of the intensity levels and the associated water levels and descriptions of expected damage, we expect lots in the high-intensity areas to have the largest discount on prices. We include this aspect by modifying the hedonic price function as we extend it by additional DiD terms. The adapted regression formula is given by Eq. (9).

$$\log P_i = \beta X_i + \theta Z_i + \sum_{\phi} \varsigma^{\phi} H_i^{\phi} + \vartheta K_i^{\tau} + \sum_{\phi} \omega^{\phi, \tau} \overbrace{(H_i^{\phi} \cdot K_i^{\tau})}^{DiD_i^{\phi, \tau}} + u_i \quad (9)$$

The variable  $H_i^{\phi}$  is binary and indicates whether a lot is located in the specific hazard zone  $\phi$ , where  $\phi \in \{\text{low, medium, high}\}$ . It is multiplied by the binary variable  $K_i^{\tau}$  that indicates whether the lot is sold after a certain point in time with  $\tau \in \{\text{Post1, Post2, Post3}\}$ .  $\omega$  is the vector of DiD parameters, i.e. our coefficients of interest. Negative significant values would indicate that lots inside a certain intensity zone  $H_i^{\phi}$  sold in the according post-treatment period ( $K_i^{\tau}$ ) are lower priced than lots outside zone  $H_i^{\phi}$ , i.e. lots sold before the event.

<sup>30</sup> However, the distance to the river is not the only factor that influences the level of flood intensity.



**Fig. 8** Robustness 1. *Left*: The main sample. *Right*: extended sample. The sample area is depicted as a convex hull around the observation units. Data: Landeshauptstadt Dresden (2019a, 2022a, c)

Regarding the before discussed DiD assumptions, however, we can only interpret the parameter of the first post-treatment period, as for the second and third post-treatment period the SUTVA does not hold.

Table 2 displays the results of the regression considering flood risk intensity levels. The regression results of the heterogeneous treatment confirm our expectations that the discount on lot prices depends on intensity.

*Post-treatment period 1* For the high intensity in the first pre-treatment period ( $DiD_{post1,high}$ ), we find a comparably large discount of 44.9% in the mean that is highly significant. For medium intensity ( $DiD_{post1,medium}$ ) the discount is smaller in the mean and insignificant. This might be due to the large confidence intervals caused by the limited number of observations for each group. For the low intensity area ( $DiD_{post1,low}$ ) we do not find a significant effect in the first post-treatment period, and the mean estimate is even positive. On the one hand, this is an interesting insight, that shows how the intensity of the expected risk influences prices. It might be a hint that not risk, as a rather abstract concept, causes the discount, but the actual damage that is to be expected. On the other hand, it gives us an idea as to why the first post-treatment period might be only slightly significant in the main analysis. In fact, the low significance can be caused by a small number of observations in the high intensity area that has been transacted in this period and a larger number of observations in the medium and low intensity areas.

*Post-treatment period 2* Just as in the main analysis, the parameters for the second post-treatment period ( $DiD_{post2,high}$ ,  $DiD_{post2,medium}$ ,  $DiD_{post2,low}$ ) cannot be interpreted due to the violation of the SUTVA, caused by the unsuitability of the available HQ 100 risk maps as proxy for the state of protection during that period. The insignificance of the parameter is therefore not the prove of the non-existence of an effect but just the artifact of the data and model.

*Post-treatment period 3* As the high intensity areas are the least likely to be protected of HQ 100 events due to their proximity to the river, we also find a significant and rather large discount for the third post-treatment period ( $DiD_{post3,high}$ ). Unfortunately this part of the investigation violates the SUTVA not only for the second, but also for the third post-treatment period. The reason for this shortcoming is, that the

intensity is only available for the state of the HQ100 area before the implementation of protection measures. For the updated versions there is no such information delivered.

Still, regarding our main results, the findings of this robustness analysis imply that we have to be careful making statements about the overall effect of flood risk on lot prices. Although a high flood risk exposure leads to a comparably large discount on lot prices, the same is not necessarily true for a low flood risk exposure, where possibly positive effects of location exceed negative effects caused by potential flooding.

**Table 2** Robustness: Heterogeneity in intensity

	<i>Dependent variable: log(Price)</i>
	<i>SEM</i>
Post1	−0.103*** (0.025)
Post2	0.006 (0.024)
Post3	0.247*** (0.028)
Treat <sub>high</sub>	0.202* (0.119)
Treat <sub>medium</sub>	0.041 (0.062)
Treat <sub>low</sub>	−0.027 (0.057)
DiD <sub>post1,high</sub>	−0.449*** (0.156)
DiD <sub>post2,high</sub>	−0.189 (0.140)
DiD <sub>post3,high</sub>	−0.381*** (0.142)
DiD <sub>post1,medium</sub>	−0.096 (0.077)
DiD <sub>post2,medium</sub>	−0.076 (0.066)
DiD <sub>post3,medium</sub>	−0.009 (0.069)
DiD <sub>post1,low</sub>	0.002 (0.070)
DiD <sub>post2,low</sub>	0.008 (0.062)
DiD <sub>post3,low</sub>	0.059 (0.068)
Controls	Yes
Lambda	0.711

**Table 2** (Continued)

Observations	Treatment	Control
N00-02 high	18	
N00-02 medium	68	531
N00-02 low	69	
N02-06 high	17	
N02-06 medium	88	965
N02-06 low	107	
N07-13 high	26	
N07-13 medium	154	1940
N07-13 low	106	
N13-17 high	27	
N13-17 medium	103	1072
N13-17 low	64	
BIC	8541.056	
AIC	8151.964	
LR Test (df = 1)	699.497***	

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

## 7.2 Extension of the sample

In our main analysis, we cut the sample with respect to the difference in altitude relative to the river Elbe. This ensures comparability of lots in the treatment group and in the control group as lots and houses in the outskirts of the city differ considerably from lots in the inner-city areas. We extend the sample of our investigation by relaxing this threshold for the altitude difference to the river Elbe. The old and new sample areas are depicted in Fig. 7 together with the 2002 floodplain. However, this does not only affect the control group as we now also include lots prone to flooding by the secondary rivers Weißeritz, south of the city center, and Lockwitzbach in the southeast. As also for the river Weißeritz there have been protection measures installed since 2002, which makes the investigation of a larger sample even more difficult and parameters are prone to be biased again due to an unstable assignment to treatment and control groups.

*Post-treatment period 1, 2 and 3* Table 3 presents the results of the regression. Compared to the results of the main analysis (see Table 1), the overall effects detected are smaller. This is true for the DiD parameter mean estimates of each post-treatment period. For the first post-treatment period, this also means, that there is no significant effect detected anymore.

We attribute this finding mainly to the fact that we now include observations in the control group which might have been flooded by secondary rivers (which are not covered in the maps we base our treatment on), and hence are not actually unaffected by the treatment, which biases the results. This bias can be slightly narrowed down looking at further inundation and flood related measures implemented on secondary rivers. Especially the river Weißeritz in the south of the city center has been adapted after the 2002 flood event. Hence, for this robustness analysis this bias is expected to be the smallest where this measure had already been implemented which is the third post-treatment period.<sup>31</sup>

In Sect. 3.3 we mention the possible moving of people from the HQ 100 areas to adjacent unaffected areas. This would mean, demand in the HQ 100 areas decreases and demand in unaffected surrounding areas would increase. Hence, a price discount for the treatment group compared to the control group could be caused by rising

**Table 3** Robustness: Extension of sample

<i>Dependent variable: log(Price)</i>		
<i>SEM</i>		
Treat	-0.023 (0.044)	
Post1	-0.119*** (0.021)	
Post2	-0.017 (0.020)	
Post3	0.259*** (0.023)	
$DiD_{post}$	-0.069 (0.053)	
$DiD_{post2}$	-0.025 (0.050)	
$DiD_{post3}$	-0.184*** (0.054)	
Controls	Yes	
Lambda	0.703	
Observations	Treatment	Control
N00-02	157	791
N02-06	216	1421
N07-13	339	3042
N13-17	227	1727
BIC	10974.304	
AIC	10604.510	
LR Test (df = 1)	896.004***	

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

<sup>31</sup> According to Landeshauptstadt Dresden (2017b) the extension of the river bed of the Weißeritz began in 2009 and was already functioning and protecting relevant areas during the 2013 flood event.

prices in the areas adjacent to the HQ 100 area rather than a price drop in the treated area. By extending the sample, we mainly add observations to the control group.

### 7.3 Disclosure of information

To test whether the discount is dependent on the actual flood or the disclosure of risk maps, we shift the date of the shock to 2004, the year when the first HQ 100 map, was published. Meaning, we assume that the disclosure of the HQ map is the actual treatment point in time, not the flood event in 2002.

The results of this investigation are shown in Table 4. All DiD parameters are to be interpreted with respect to the reference period. This reference period, the pre-treatment period, now ranges from 2000 until 2004 and therefore deviates from the pre-treatment period of the main analysis and all other robustness estimations.

If however, the flood event of 2002 is the actual treatment, setting the pre-treatment period from 2000 to 2004, would violate the assumption about the absence of a pre-treatment effect.

*Post-treatment period 1* The first post-treatment period now ranges from 2004 until 2007. The corresponding parameter ( $DiD_{2004-2007}$ ) in Table 4 is smaller in magnitude than the DiD parameter ( $DiD_{post1}$ ) in Table 1 and insignificant. We conclude that the relevant shock is the actual flood event rather than the publication of risk maps due to the previously explained violated assumption on the absence of a pre-treatment effect.<sup>32</sup> This might appear to contradict Votsis and Perrels (2016) who explicitly investigate the public disclosure of flood risk maps separated from actual flood events. However, we assume that – at least in our case – the information about the risk is spread at the date of the first event when aerial views were taken and published in the media.

*Post-treatment period 2 and 3* Just as in the main analysis, the second post-treatment period cannot be interpreted and hence will be left out here. For the third post-treatment period we find a similar effect to the first post-treatment period. Especially the magnitude of the effect here is reduced drastically. Again, we attribute this to the flood event being the actual treatment rather than the disclosure of the maps.

<sup>32</sup> A vanished significance might also be explained by the reduced number of observations in this period, however, it might not necessarily explain the varying of the magnitude of the parameter.

**Table 4** Robustness: Disclosure of risk maps

Dependent variable: $\log(\text{Price})$		
SEM		
Treat	−0.066*	
	(0.036)	
Post1	−0.052**	
	(0.026)	
Post2	0.051***	
	(0.019)	
Post3	0.329***	
	(0.023)	
$DiD_{2004-2007}$	0.020	
	(0.059)	
$DiD_{2007-2013}$	0.014	
	(0.045)	
$DiD_{2013-2017}$	−0.147***	
	(0.048)	
Controls	Yes	
Lambda	0.704	
Observations	Treatment	Control
N00-04	261	1070
N04-07	112	470
N07-13	339	2294
N13-17	227	1281
BIC	8484.01	
AIC	8148.586	
LR Test (df = 1)	690.722***	

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

#### 7.4 Investigation of spatial spillovers

To address the potential existence of spatial spillovers, we extended our SEM to an SDEM, hence, add lagged terms of the explanatory variables. The according regression equation is provided by Eq. (10).

$$\begin{aligned}
 \log P_i = & \beta X_i + \theta Z_i + \varsigma H_i + \sum_{\tau} \vartheta^{\tau} K_i^{\tau} + \sum_{\tau} \omega^{\tau} \overbrace{(H_i \cdot K_i^{\tau})}^{DiD_i^{\tau}} \\
 & + \delta W X_i + \rho W Z_i + \zeta W H_i + \sum_{\tau} \eta^{\tau} W K_i^{\tau} + \sum_{\tau} \nu^{\tau} \overbrace{W(H_i \cdot K_i^{\tau})}^{WDiD_i^{\tau}} \quad (10) \\
 & + \lambda W u_j + \epsilon_i
 \end{aligned}$$



**Table 5** Robustness: SDEM

	<i>Dependent variable: log(Price)</i>	
	<i>SEM</i> (1)	<i>SDEM</i> (2)
Treat	−0.006 (0.046)	−0.003 (0.047)
Post1	−0.099*** (0.025)	−0.097*** (0.026)
Post2	0.002 (0.024)	0.001 (0.024)
Post3	0.279*** (0.027)	0.289*** (0.028)
$DiD_{\text{post1}}$	−0.092* (0.055)	−0.075 (0.056)
$DiD_{\text{post2}}$	−0.038 (0.052)	−0.020 (0.053)
$DiD_{\text{post3}}$	−0.198*** (0.055)	−0.210*** (0.056)
lag.Treat		−0.013 (0.263)
lag.Post1		0.168 (0.191)
lag.Post2		0.005 (0.167)
lag.Post3		0.256 (0.192)
$lag.DiD_{\text{post1}}$		0.136 (0.379)
$lag.DiD_{\text{post2}}$		0.182 (0.305)
$lag.DiD_{\text{post3}}$		−0.537 (0.349)
Controls	Yes	Yes
Lambda	0.706	0.604
Observations	Treatment	Control
N00-02	157	552
N02-06	216	988
N07-13	339	2294
N13-17	227	1281
BIC	8458.263	8737.455
AIC	8122.839	8100.150
LR Test (df = 1)	700.236***	366.743***

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

The results are reported in Table 5. Column 1 shows the results of the SEM model for the main analysis and column 2 gives the results of the SDEM.<sup>33</sup>

*Post-treatment period 1, 2 and 3* We find, that the parameters of the spatially lagged DiD terms ( $lag.DiD_{post1}$ ,  $lag.DiD_{post2}$ ,  $lag.DiD_{post3}$ ) are not significant in our investigation, which is contrary to the findings of Pommeranz and Steininger (2020). Interestingly the magnitude of the mean estimate for the third post-treatment period increases, whereas the parameter of the first post-treatment period shrinks further and comes out as insignificant in the SDEM. Apart from this, the overall results appear to be robust to the extension of the model by spatially lagged terms.<sup>34</sup>

However, it remains not entirely clear what would be captured by significant indirect effects, meaning the spatially lagged DiD terms in an SDEM. The spatially lagged indicator variable for the assignment to the treatment group reflects how large the share of neighboring properties is that lies within the respective HQ 100 zone. However, an increasing share of neighboring properties located in the hazard zone also increases the probability of the lot itself being located in the HQ 100 zone. This leads to multicollinearity affecting our variables of interest and lowering the precision of the estimates. In conclusion, what might be detected or interpreted as indirect effects of flood risk on property prices might simply be the artifact of two variables basically capturing the same effect.

Still a relevant aspect might be that the spatially lagged variables could be considered a proxy for the expected damage to infrastructure and amenities in the vicinity of the own property in the case of a flood event. This is generally an interesting effect and desirable to disentangle from the impact of the own property's risk to be flooded. However, both effects correlate strongly. Hence, the SDEM is not considered to be suitable for this task by the authors of this paper.

## 7.5 Variation of the spatial weights matrix

In our main analysis we set the radius for the definition of the spatial weights matrix to 300 m. Selecting a smaller radius, e.g. 200 m, causes the sample size to decrease as observations are dropped if no neighbors are available. However, selecting a larger radius can be reasonable and is therefore investigated in the following, with a radius of 500 m.

*Post-treatment period 1, 2 and 3* The results in Table 6 show that the discount on transaction prices in the first post-treatment period ( $DiD_{post1}$ ) increases only slightly and significance remains low. Also in this investigation, the second post-treatment period cannot be interpreted, as the SUTVA does not hold for this period. Just like the first post-treatment period, also the DiD parameter of the third post-treatment

<sup>33</sup> The full regression results of both, SEM and SDEM can be found in Table 9 in the Appendix.

<sup>34</sup> The same is true for the parameters of the control variables, as shown in table 9. Except for the distances to the river and to the motorway, no changes in the significant of the parameters are detected. Interestingly spatial spillovers appear to exist in case of street noise, which turns out to be insignificant in its direct effect.

**Table 6** Robustness: Variation of spatial weights matrix. Distance 500m

<i>Dependent variable: log(Price)</i>		
<i>SEM</i>		
Treat	−0.006 (0.045)	
Post1	−0.098*** (0.025)	
Post2	0.004 (0.024)	
Post3	0.285*** (0.027)	
$DiD_{post1}$	−0.100* (0.055)	
$DiD_{post2}$	−0.046 (0.052)	
$DiD_{post3}$	−0.211*** (0.055)	
Controls	Yes	
Lambda	0.813	
Observations	Treatment	Control
N00-02	157	552
N02-06	216	988
N07-13	339	2295
N13-17	227	1281
BIC	8518.656	
AIC	8183.224	
LR Test (df = 1)	646.764***	

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

period ( $lag.DiD_{post3}$ ) is stable in terms of significance and increases only slightly in magnitude.

Overall the variation of the distance used to create the dnn spatial weight matrix confirms the findings of the main analysis. Indeed, only one observation overall is added to the sample, which was excluded before due to no detected neighbors in a 300m radius.

## 8 Conclusion

While the intuition of flood risk capitalizing into lot prices is straightforward, the actual prove appears to be rather challenging. The reason is that even for an exogenous, unforeseen event there are various sources of heterogeneity that also appear to be individual to each study area.

At least for our study area, we provide evidence for a negative effect of flood risk on lot prices, that occurs immediately after an exogenous, unforeseen flood event.

We find this effect to vanish over time only if we neglect adaption measures that have been implemented in the aftermath of the initial flood event. Once we control for this heterogeneity over time of the treatment group in the post-treatment periods, the discount remains present. Still, as no information on adaption measures is provided in most studies, we cannot actually approve or deny the ‘forgetting effect’ as found in Bin and Landry (2013) or Zhang (2016), but in our case it is mainly explained by protection.

Regarding the recurring of events, we find an even more significant effect, that is even slightly larger in the mean for the third post-treatment period, meaning after the 2013 flood event. We attribute this finding to the fact that lots which are at this point still exposed to flood risk, are located in areas that are technically only difficult to protect or cannot be protected at all. In addition those lots are on average exposed to a higher flood risk intensity.

This impact of intensity is what we focus on in our robustness section. We find that flood intensity, i.e. spatial heterogeneity of the treatment group, is generally decisive for the magnitude of the discount on lot prices. Intuitively lots with a higher expected flood intensity show a larger discount than lots with a lower expected intensity. This is confirmed by our findings. For lots inside the low intensity zone, the benefits of being located at the river might even outweigh the negative impact caused by flood risk.

Our robustness analysis also reveals that in our setting the discount on lots exposed to flood risk does not appear after the disclosure of the risk through published maps as found in Votsis and Perrels (2016), but right after the actual event. We therefore consider the 2002 flood event the risk revealing shock.

Spatial spillovers as found in Pommeranz and Steininger (2020) cannot be confirmed by our findings. Still, potentially affected amenities that might be captured by spatial spillover effects remain an interesting research question.

What is also yet to be discovered is the actual origin of the detected discount on lot prices. The results of our study do not reveal whether the discount in lot prices arises from the actual damage after the flood or the risk, meaning the expected damage or the costs for insurance. This is due to the naturally high correlation of the actual floodplain and the hazard zones. Although we expect the detected effect to be rather conservative as we include lots that are affected by higher risk and therefore higher damage and lots that face medium or lower risk and respectively medium or low damage.

## 9 Appendix

### 9.1 Data

Table 7 presents the descriptive statistics for the initial metric variables used in the regression analyses. In addition the nominal variables as well as their shares in the sample are summarized in Table 8. In the model, the transaction price as dependent variable is logarithmized, to approximate a normal distribution. Additionally, all metric explanatory variables are logarithmized. A squared term is added for the

**Table 7** Descriptive statistics of metric variables

Statistic	<i>N</i>	Mean	St. Dev.	Min	Max
Transaction price* [tsd. Euro]	6,054	1,834.72	7,772.80	3.65	105,676.78
Distance city center [m]	6,054	4,267.59	2,589.07	0.00	11,596.20
Distance Elbe [m]	6,054	1,010.93	655.64	22.00	3,360.00
Distance tram [m]	6,054	439.25	531.88	7.52	2,768.69
Distance motorway [m]	6,054	3,761.96	1,781.30	38.86	7,588.99
Living space [square m]	6,054	1,036.89	10,978.87	36.00	829,829
Total space [square m]	6,054	1,340.33	2,717.03	18.00	54,057
Altitude [m above sea level]	6,054	114.06	2.43	105.00	120.00
Levels [number]	6,054	3.23	1.39	1.00	17.00

Note: \* Transaction prices adjusted to 2015 Euro

**Table 8** Descriptive statistics of nominal/ordinal variables

Statistic	<i>N</i>	Categories	Number	Share
Condition	6,054	Not stated	1351	0.22
		Renovated	2128	0.35
		Partially renovated	871	0.14
		Not renovated	1704	0.28
Type of building	6,054	Commercial (COM)	995	0.16
		Multi-family (MFH)	3672	0.61
		Single-family (SFH)	1387	0.23
Year of construction	6,054	< 1951	4455	0.74
		1951–1990	211	0.03
		> 1990	1388	0.23
Rented	6,054	Yes	1502	0.25
		No	4552	0.75
Seller is relative	6,054	Yes	86	0.01
		No	5968	0.99
Treat	6,054	Yes	939	0.16
		No	5115	0.84
Noise street	6,054	Yes	2058	0.34
		No	3996	0.66
Noise rail	6,054	Yes	1677	0.28
		No	4377	0.72

logarithmized terms of the altitude, the living space and the total space. To reduce multicollinearity, the squared terms are built of the deviation from the mean of the corresponding variable, rather than the simple squared term.<sup>35</sup>

<sup>35</sup> As an example, the living space is included in the following way:  $\log P = \dots + \beta_1 \text{livingspace} + \beta_2 \left( \frac{\text{livingspace}}{\text{mean}(\text{livingspace})} \right)^2 + \dots$

## 9.2 Results tables

The following Table 9 represents the full regression results of the SEM (Column 1) as well as the full results of the SDEM (Column 2). Additionally the regression results of the baseline OLS model without consideration of spatial dependence apart from spatial fixed effects are reported in Table 10 (Column 1) and juxtaposed with the SEM model of the main analysis (Column 2).

**Table 9** Results: Main – full table

	<i>Dependent variable: log(Price)</i>	
	<i>SEM</i> (1)	<i>SDEM</i> (2)
Rented	0.087*** (0.017)	0.091*** (0.018)
log(altitude)	−0.327 (0.632)	−0.022 (0.649)
Treat	−0.006 (0.046)	−0.003 (0.047)
Post1	−0.099*** (0.025)	−0.097*** (0.026)
Post2	0.002 (0.024)	0.001 (0.024)
Post3	0.279*** (0.027)	0.289*** (0.028)
Seller is relative	−0.651*** (0.051)	−0.637*** (0.053)
log(Dist Elbe)	−0.039 (0.024)	−0.085** (0.043)
log(Dist tram)	−0.008 (0.013)	−0.002 (0.015)
log(Dist motorway)	0.142** (0.060)	0.224* (0.123)
Noise street	−0.018 (0.015)	−0.009 (0.015)
Noise rail	−0.099*** (0.025)	−0.076*** (0.026)
Type is MFH	−0.291*** (0.025)	−0.296*** (0.025)
Type is SFH	−0.056** (0.022)	−0.066*** (0.022)
Year of construction > 1990	0.728*** (0.060)	0.700*** (0.060)
Year of construction < 1951	0.021 (0.038)	0.005 (0.038)

**Table 9** (Continued)

	<i>Dependent variable: log(Price)</i>	
	<i>SEM</i> (1)	<i>SDEM</i> (2)
log(Living space)	0.405*** (0.014)	0.404*** (0.014)
log(Living space/mean(Living space)) sqrd	−0.008* (0.005)	−0.006 (0.005)
log(Total space)	0.506*** (0.011)	0.506*** (0.011)
log(Total space/mean(Total space)) sqrd	0.033*** (0.005)	0.032*** (0.005)
Levels	0.205*** (0.020)	0.213*** (0.021)
Levels sqrd	−0.008*** (0.002)	−0.010*** (0.002)
Condition renovated	0.447*** (0.051)	0.429*** (0.051)
Condition partially renovated	0.025 (0.052)	0.007 (0.053)
Condition not renovated	−0.590*** (0.051)	−0.613*** (0.052)
$DiD_{post1}$	−0.092* (0.055)	−0.075 (0.056)
$DiD_{post2}$	−0.038 (0.052)	−0.020 (0.053)
$DiD_{post3}$	−0.198*** (0.055)	−0.210*** (0.056)
lag.Rented		0.151 (0.125)
lag.log(altitude)		−2.468 (1.972)
lag.Treat		−0.013 (0.263)
lag.Post1		0.168 (0.191)
lag.Post2		0.005 (0.167)
lag.Post3		0.256 (0.192)
lag.Seller is relative		0.303 (0.400)
lag.log(Dist Elbe)		0.027 (0.057)

**Table 9** (Continued)

	<i>Dependent variable: <math>\log(\text{Price})</math></i>	
	<i>SEM</i> (1)	<i>SDEM</i> (2)
lag.log(Dist tram)		−0.041 (0.031)
lag.log(Dist motorway)		−0.217 (0.150)
lag.Noise street		−0.147** (0.064)
lag.Noise rail		−0.102 (0.066)
lag.Type is MFH		−0.235* (0.138)
lag.Type is SFH		−0.142 (0.103)
lag.Year of construction > 1990		−0.907*** (0.280)
lag.Year of construction < 1951		−0.251 (0.170)
lag.log(Living space)		0.166** (0.070)
lag.log(Living space/ mean(Living space)) sqrd		0.037* (0.021)
lag.log(Total space)		−0.044 (0.049)
lag.log(Total space/mean(Total space)) sqrd		−0.038* (0.021)
lag.Levels		0.039 (0.080)
lag.Levels sqrd		−0.001 (0.006)
lag.Condition renovated		−0.812*** (0.253)
lag.Condition partially reno- vated		−0.753*** (0.270)
lag.Condition not renovated		−0.943*** (0.262)
lag. $DiD_{\text{post1}}$		0.136 (0.379)
lag. $DiD_{\text{post2}}$		0.182 (0.305)
lag. $DiD_{\text{post3}}$		−0.537 (0.349)



**Table 9** (Continued)

	<i>Dependent variable: log(Price)</i>	
	<i>SEM</i> (1)	<i>SDEM</i> (2)
Constant	6.440** (3.022)	19.169* (10.207)
ZIP Codes	Yes	Yes
Lambda	0.706	0.604
Observations	Treatment	Control
N00-02	157	552
N02-06	216	988
N07-13	339	2294
N13-17	227	1281
BIC	8458.263	8737.455
AIC	8122.839	8100.150
LR Test (df = 1)	700.236***	366.743***

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

**Table 10** Baseline OLS estimation results and SEM

	<i>Dependent variable: log(Price)</i>	
	OLS	SEM
Rented	0.077*** (0.019)	0.087*** (0.017)
log(altitude)	−0.942* (0.556)	−0.327 (0.632)
Treat	−0.0001 (0.048)	−0.006 (0.046)
Post1	−0.083*** (0.027)	−0.099*** (0.025)
Post2	0.004 (0.025)	0.002 (0.024)
Post3	0.319*** (0.029)	0.279*** (0.027)
Seller is relative	−0.668*** (0.056)	−0.651*** (0.051)
log(Dist Elbe)	−0.048*** (0.012)	−0.039 (0.024)
log(Dist tram)	−0.027*** (0.009)	−0.008 (0.013)
log(Dist motorway)	0.068** (0.029)	0.142** (0.060)
Noise street	−0.047*** (0.015)	−0.018 (0.015)
Noise rail	−0.162*** (0.020)	−0.099*** (0.025)

**Table 10** (Continued)

	<i>Dependent variable: log(Price)</i>	
	OLS	SEM
Type is MFH	−0.320*** (0.026)	−0.291*** (0.025)
Type is SFH	−0.079*** (0.022)	−0.056** (0.022)
Year of construction > 1990	0.631*** (0.061)	0.728*** (0.060)
Year of construction < 1951	−0.034 (0.038)	0.021 (0.038)
log(Living space)	0.458*** (0.015)	0.405*** (0.014)
log(Living space/mean(Living space)) sqrd	0.012** (0.005)	−0.008* (0.005)
log(Total space)	0.492*** (0.011)	0.506*** (0.011)
log(Total space/mean(Total space) sqrd	0.018*** (0.005)	0.033*** (0.005)
Levels	0.184*** (0.021)	0.205*** (0.020)
Levels sqrd	−0.003 (0.002)	−0.008*** (0.002)
Condition renovated	0.373*** (0.052)	0.447*** (0.051)
Condition partially renovated	−0.040 (0.054)	0.025 (0.052)
Condition not renovated	−0.672*** (0.052)	−0.590*** (0.051)
$DiD_{post1}$	−0.100* (0.059)	−0.092* (0.055)
$DiD_{post2}$	−0.081 (0.056)	−0.038 (0.052)
$DiD_{post3}$	−0.273*** (0.059)	−0.198*** (0.055)
Constant	10.183*** (2.665)	6.440** (3.022)
Controls	Yes	Yes
Lambda		0.706
Observations	treatment	control
N00-02	157	552
N02-06	216	988
N07-13	339	2294
N13-17	227	1281

**Table 10** (Continued)

	<i>Dependent variable: log(Price)</i>	
	OLS	SEM
Adjusted R <sup>2</sup>	0.851	
BIC	9149.791	8458.263
AIC	8821.076	8122.839
Residual Std. Error	0.499 (df = 6006)	
F Statistic	735.931*** (df = 47; 6006)	
LR Test		700.236*** (df = 1)

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$

**Funding** Not applicable

**Consent to participate** Not applicable

**Consent for publication** Not applicable

**Availability of data and materials** The datasets generated during and/or analysed during the current study are not publicly available due to data privacy but are available from the corresponding author on reasonable request.

**Code availability** The Code is available from the corresponding author on request.

**Author Contribution** All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Sophie Häse. The first draft of the manuscript was written by Sophie Häse and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

**Funding** Open Access funding enabled and organized by Projekt DEAL.

## Declarations

**Conflict of interest** Not applicable

**Ethical standards** Not applicable

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