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Land Subsidence, Flood Risk, and Property Prices[*]

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Abstract

This paper examines the effect of land subsidence – the gradual sinking of the Earth's surface – on property values. Subsidence can negatively affect real estate by damaging building foundations and increasing vulnerability to flooding. Using detailed property transaction data from the Netherlands, combined with high-resolution geospatial data on both current and projected subsidence and flood risk, we find that properties currently experiencing subsidence sell at a 0.8% discount when built on foundations susceptible to damage. Additionally, flood-prone properties projected to experience future subsidence sell for 1.5% less. Compared to the actual costs and occurrence of these risks, our findings suggest that homeowners tend to underestimate the risks associated with foundation damage while overestimating the threat of future flooding.

Keywords — Land subsidence, property prices, climate risk, risk perception

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1 Introduction

About 1.6% of the global land surface is sinking (Herrera-García et al., 2021). This process is known as land subsidence and can be caused by natural and anthropogenic drivers such as groundwater extraction, tectonic motions, or soil degradation (Murfin and Spiegel, 2020). Due to climate change, extreme droughts will become more likely in the future, putting additional pressure on groundwater levels, further exacerbating the severity of land subsidence (Herrera-García et al., 2021). Land subsidence is concentrated in densely populated coastal areas, for example, in Asia along the eastern coast of China and around the Indonesian capital of Jakarta, or in the United States of America (US) along the Gulf of Mexico and in California (Murfin and Spiegel, 2020; Herrera-García et al., 2021). Subsidence can directly damage the foundation of buildings and infrastructure (Herrera-García et al., 2021). Furthermore, the lowering of the ground interacts with the risk of flooding. Even small changes in land subsidence, particularly as they add up over time, can lead to large increases in flood risk and associated damages (Ohenhen et al., 2024).[1]

This paper aims to examine the effect of land subsidence and flood risk on residential property prices. Although climate impacts are not limited to housing, real estate is considered one of the largest asset classes, with about 380 trillion in outstanding value by 2022 globally, of which housing accounts for about 75% (Tostevin and Rushton, 2023). That is, the potential impacts are large, and thus there is significant policy interest in those impacts. Moreover, to the extent that households are aware of these risks, we would expect them to be factored into property prices. Our specific contribution lies in examining the interaction between subsidence and flooding risks, and in assessing whether households tend to overestimate or underestimate these risks based on the actual associated costs and the information available to them. While there has been research on the perception of flood risk (e.g., Bosker et al., 2019; Giglio et al., 2021b; Niu et al., 2025) and the effect of sea level rise on property prices (Murfin and Spiegel, 2020), less is known about the perception of subsidence and its effect on property prices.

Due to its long-lasting history with both land subsidence and flood risk, our analysis is based on housing transaction data from the Netherlands between 2010-2021 and detailed maps on subsidence and flood risk. The housing transaction data covers up to 95 percent of all housing transactions in the Netherlands. To capture historical subsidence, we use satellite measurements

[1] The hydrology literature, for example, uses root functions to map inundation depths into flood damages, as this class of functions has the best empirical fit (Sieg and Thieken, 2022; Endendijk et al., 2023).

of 305 million measurement points that cover the entire Netherlands, and projections of future subsidence are based on the Atlantis Model (Bootsma et al., 2020), which predicts subsidence at a very granular level until 2050. This level of detail is important because both land subsidence and flood risks tend to occur near rivers and the coast (i.e., clay and peat soils).

The variation in house prices, flood risk, and land subsidence allows us, like previous studies (e.g., Murfin and Spiegel, 2020; Yoo and Perrings, 2017; Yoo and Frederick, 2017; Willemsen et al., 2020; Premchand et al., 2024), to control for detailed location fixed effects. We extend this approach using a border regression discontinuity design along the lines of Black (1999) and Gibbons et al. (2013). In addition, the historical versus future subsidence, but also online search behavior around the introduction of the current subsidence maps allows us to look more closely at the effect of salience as, for example, suggested by Giglio et al. (2021b) and Niu et al. (2025) in the case of flood risk. By comparing actual estimated costs with households' perceived costs, we can further explore whether subsidence and flood risk are priced appropriately. This informational story is important for policy makers, and it can explain some of the mixed findings about the pricing of these types of climate risks in the literature.

We find evidence of both *direct* and *indirect* price effects of subsidence. Properties that are currently subsiding by more than 3.3 mm per year – the cut-off at which subsidence begins to lead to foundation damage – trade at a discount of 0.8% if built on a foundation prone to damage. Flood-prone properties predicted to subside by more than 10 cm by 2050 obtain 1.5% lower prices. These results imply that it is important to simultaneously model the effect of flood risk and land subsidence on house prices. Furthermore, based on estimates of the number of houses most at risk (about 17% of houses in the Netherlands), homeowners seem to underestimate the probability of foundation damages as the implied probability of minor foundation damage within this subsample is only 23% while it should be around 100%. Instead, they overestimate the risk of flooding (i.e., in line with Bosker et al., 2019) thinking that flooding occurs every 70 years – within their own lifetime – instead of every 100,000 years as indicated by the Dutch government. This apparent misperception of risks underlines the benefits of stricter climate risk disclosure for real estate transactions.

In line with this conclusion, our results further show that an increase in a salience (online search volume) index by one standard deviation further decreases the price of properties currently subsiding by 0.8%. The index peaks at the introduction of the subsidence maps. However, the decrease does not affect the price of the properties most at risk, i.e. properties with a vulnerable foundation and flood-prone properties. Given that these households did not adequately price these risks in the first place, this provides further evidence that information on subsidence risk is not properly priced.

The paper relates to a growing literature on land subsidence and flood risk. Murfin and Spiegel (2020) look at the level of elevation of residential properties in the US and the relative sea level rise (RSLR) based on historical trends in regional mean sea levels. RSLR is expected to mainly proxy for variations in vertical land motion. Murfin and Spiegel (2020) do not find detectable effects of inundation on property prices. Keenan et al. (2018) analyze real estate and sea level rise in Miami-Dade County, Florida, and find that homes located at higher elevations experienced greater price appreciation. Yoo and Perrings (2017) and Yoo and Frederick (2017) study subsidence in Maricopa County, Arizona. Yoo and Frederick (2017) find a decrease in property values of 1.8%, while Yoo and Perrings (2017) find a decrease of about 10% for current subsidence and 7% for future subsidence. Willemsen et al. (2020) investigate subsidence in the Dutch cities of Rotterdam and Gouda and find a 6% decrease in house prices but only for uniform subsidence. Premchand et al. (2024) study subsidence in the Green Heart, a relatively high-priced coastal region in the Netherlands and find that properties exposed to subsidence trade at a discount of 2.5%-5%, which is more pronounced for older properties with a more exposed foundation. To our knowledge, there are currently no papers that combine detailed information on current and future land subsidence with flood risk data to examine the effect of land subsidence on property prices.

Our paper further relates to the literature on climate and salience. Baldauf et al. (2020) and Bakkensen and Barrage (2022) suggest that buyers might hold optimistic beliefs about climate change and the related risks. Therefore, agents are not accurately pricing climate risks. Recent estimates suggest that the stock of flood-prone houses in the United States is overvalued by $32-$237 billion (Hino and Burke, 2021; Gourevitch et al., 2023). Moreover,Giglio et al. (2021b) use the written description of listed properties to create a climate attention index and find that house prices in flood-prone areas decline relative to non-flood-prone areas if the index is higher. Instead, using aggregate zip code level data, Bosker et al. (2019) find that flood-prone properties in the Netherlands trade at a discount of 1%, which implies that market participants overestimate the probability of flooding, at least compared to official claims about the state of flood defenses. Niu et al. (2025) use data from Dordrecht, a city in the Netherlands, between 2005 and 2017 and find that actual flooding decreases property prices and that better flood risk information leads to larger sale price-list price discounts. In addition, other works have emphasized the role of sophistication. Bernstein et al. (2019) find that sea level rise is only priced in the non-owner occupied segment of the US housing market in which commercial investors are more experienced and have more resources to assess risks. This argument is echoed by studies concerned with other forms of commercial real estate (Addoum et al., 2024; Fang et al., 2024; Holtermans et al., 2024; Ling et al., 2024). By looking at current versus future land subsidence, as well as online search behavior, we can examine the extent to which salience affects the effect of land subsidence on property values.

The remainder of this paper proceeds as follows. Section 2 provides background information on land subsidence, foundation types, and flood risk in the Netherlands. In Section 3, we describe the data. Section 4 outlines our identification strategy. Results are presented in Section 5, and implications in Section 6. Finally, Section 7 concludes.

2 Causes and Consequences

2.1 Land Subsidence

Land subsidence refers to the lowering of land surfaces due to anthropogenic and natural processes (Dinar et al., 2021). The drivers include groundwater extraction, bedrock dissolution, tectonic motions, and soil degradation (Murfin and Spiegel, 2020). In total, 1.6% of the global land surface is affected by land subsidence. As subsidence is concentrated in densely populated areas with intensive agriculture, affected areas host 12% of global GDP and are home to 484 million people. The most affected areas include South and East Asia, the coasts of California and the Gulf of Mexico in the US and coastal regions in Europe (Herrera-García et al., 2021).

The Netherlands is the most affected country in Europe (Herrera-García et al., 2021). Yearly costs related to land subsidence are estimated to be up to €3.5 billion (Bucx et al., 2015). This estimate includes costs related to the maintenance of existing structures and infrastructure as well as increased construction costs for new structures. In the Netherlands, the main driver of subsidence is the dehydration of soft soils such as peat and clay. These grounds often have high groundwater levels and need to be dehydrated in order to support building structures or heavy machinery for agriculture. Depending on the type of soil, subsidence can be sustained for an extensive period of time (Erkens et al., 2016). Erkens et al. estimate that since 1,000 AD, coastal peatlands in the Netherlands have on average subsided by 1.9 metres. About one third of this subsidence can be explained by the exploitation of peat as fuel and the remaining two thirds are caused by dehydration. Partly due to this historic subsidence, 26% of the Netherlands' land surface is located below sea level today.

A second driver is the extraction of minerals, which is mainly relevant in the natural gas fields in the province of Groningen. The largest gas field is about 900 square kilometres large and located 3 kilometres below the surface (Koster and van Ommeren, 2015). The exploitation of natural gas leads to subsidence in the deep soil several kilometres below the surface, which causes seismic activity and, as a result, earthquakes. These earthquakes negatively affect property prices (Koster and van Ommeren, 2015). As subsidence related to dehydration compresses the soil close to the surface, this type of subsidence does not cause earthquakes.

Subsidence affects the vicinity of a property as well as the property itself. Therefore, one would expect subsidence to be capitalised in transaction prices. In principle, the potential impact of subsidence on property prices is twofold. First, subsidence has a *direct* effect that manifests in damages to the foundation of a property (Hommes et al., 2023). Second, there is an *indirect* effect that results from the interaction between subsidence and flood risk (Daniel et al., 2009; Ohenhen et al., 2024). Properties that already are at risk of flooding will face higher inundation depths, resulting in larger expected damages. Furthermore, houses that are currently not at risk of flooding might become prone to flood risk due to subsidence. These effects will be further discussed in the following sections.

2.2 Foundation Damage

Subsidence can have *direct* effects by leading to damages to the property's foundation. In the Netherlands, an estimated one million properties are potentially affected by foundation damages (Hommes et al., 2023). In case of minor damages to the foundation, repair costs are likely going to be below €10,000 (Kok and Angelova, 2020). However, in severe cases, repair costs can range from €50,000 - 100,000 depending on the size of the property (Hommes et al., 2023). These costs are non-insurable and buyers rarely know about the condition of the foundation when buying a property (Hommes et al., 2023).[2] Therefore, it seems likely that potential damages will be capitalized into the transaction price. Although we do not have information about the exact

[2]In the Netherlands, sellers of a property can opt to include a "foundation clause" in the purchasing contract. This clause protects the seller from liabilities, if foundation damages occur and no prior knowledge about the damage can be proven. Hommes et al. (2023) find that properties with a stated foundation clause sell at a 2% discount, which would be consistent with an expected probability of foundation damages of about 20%.

damage to foundations due to land subsidence, it heavily depends on the type of foundation.

There are three prevalent types of foundations in the Netherlands (Costa et al., 2020): pole foundations, shallow foundations, and concrete foundations. Pole foundations are common in areas with high groundwater levels, which are predominantly found in the north and west of the Netherlands. Properties with pole foundations are built on a set of wooden poles that are laid out below groundwater. When the groundwater lowers due to subsidence or droughts, the poles come in contact with oxygen, which leads to the growth of fungi. These fungi lead to timber pile degradation, a process that is also known as pole rot. The exact speed and severity depend on many factors including the size of the poles and the type of wood (Costa et al., 2020). The share of pole foundations by neighbourhood is shown in Appendix Figure B.1(a). Pole foundations mainly occur near the northern and southwestern coasts of the Netherlands. In these areas, groundwater levels are often high so that buildings need to be erected on a foundation of wooden poles.

Shallow foundations, or natural foundations, are more common in areas with lower groundwater levels. Shallow foundations transfer most of the weight of a structure onto the earth near the surface. If the land on which the structure rests subsides at different rates, these foundations are prone to differential settlement. Differential settlement can lead to damages in the construction such as cracks along the walls (Costa et al., 2020). The spatial distribution of shallow foundations is shown in Appendix Figure B.1(b). Shallow foundations are prevalent in most of the Netherlands.

Concrete foundations, on the other hand, are more robust and not prone to foundation damages, even when the land beneath them is subsiding. Although concrete foundations were already used in the beginning of the 20th century, they became widely used in the 1980s due to a combination of technological advancement, regulatory changes, and urban development needs. In the 1980s, stricter building codes were introduced that required more durable and long-lasting foundations. There was also rapid urbanization in the Netherlands, particularly in its urban core. Furthermore, there was increased prefabrication and mechanization in building, and concrete was very useful in that respect. As a consequence, all properties built in the Netherlands after 1975-1980 are extremely likely to possess a concrete foundation (Klimaateffectatlas, 2021). We will utilize this variation to measure the effect of historical subsidence on property values.

2.3 Flood Risk

The Netherlands have an extensive coastline and are located in between several major rivers, which makes the country particularly prone to floods. Its cultural landscape has been shaped by the interplay of subsidence and flood risk for centuries. Dehydration of soft soils commenced in the middle ages, leading to subsidence and increasing the relative sea levels. Major floods were reported as early as the 13^{th} century, necessitating the construction of the first flood defenses. The invention of windmills and sluices in the 17^{th} century made drainage of wet soils more efficient and exacerbated subsidence. At the same time, flood defenses improved and became more secure, which allowed a larger share of the population to settle in flood-prone areas. The last major flood resulting from the breaching of sea dikes was the spring tide disaster of 1953, which cost the lives of 1,835 people (Daniel et al., 2009) and led to migration away from flood-prone areas (Husby et al., 2014).

After this disaster, the Dutch government intensified its flood mitigation efforts. With the Delta Program, the flood defense infrastructure was updated and extended (Niu et al., 2025). Today, the Dutch government maintains about 3,750 km of dikes and 1,500 km of primary waterworks. The €1.1 billion that is spent on upkeep each year is financed out of the general government budget (Bosker et al., 2019). Furthermore, the government increased its efforts to educate the population about potential risks. To this end, the Climate Impact Atlas (*in Dutch: Klimaateffectatlas*) provides maps on the spatial distribution of flood and other climate risks (Niu et al., 2025). Several of these maps are used as data sources in the empirical analysis.

Historically, private insurers do not cover flood damages. Instead, the government was responsible for reimbursing flood-related damages. This insurance regime resulted from the spring tide disaster of 1953, which caused damages that were so immense that private insurers could not have compensated them. Insurance policies were reformed after the Meuse floods in the 1990s. Since then, private insurance covers flood damages caused by heavy rainfall. Damages caused by flooding from the sea and rivers not originating in the Netherlands continue to be excluded from insurance policies. The "Compensation of Damages due to Disasters" Act (WTS) regulates that the Dutch government is only responsible for compensating damages that are not insurable under private insurance (Bruggeman and Faure, 2018) and which are classified as a national disaster. However, the extent to which the government reimburses damages is unclear and varies between different flood events. Daniel et al. (2009) find that compensations after the Meuse floods in the 1990s (before the WTS was introduced) were rather generous. On the other hand, Bosker et al. (2019) point out that the government only reimbursed half of the damages caused by a small-scale flood event in the province of Utrecht. Of the damages caused by the Western European Flood of 2021 in the province of Limburg €224 million were covered by insurers and €104 million were compensated under the WTS (Kok et al., 2023).

3 Data

3.1 Transactions Data

Data on property transactions is collected by the *Dutch Association of Realtors* (NVM) and provided by *Brainbay*. The data set covers transaction prices, property characteristics and geocoded locations of 3.8 million properties sold between 1990 and 2021. As most variables on climate risks are only available for recent years, we restrict the sample to the period from 2010 to 2021. This restriction leaves around 1.5 million properties. We exclude a very small number of observations for which the exact location is unknown ($< 0.05\%$). Furthermore, we exclude properties for which the recorded transaction price was below €10,000 or above €2.5 million ($< 0.001\%$). The coverage of the NVM data over the relevant period is very good. Dröes and Koster (2023) compare the transactions covered in the NVM dataset and recorded in the land registry and find that the yearly coverage for the period from 2010 to 2015 is between 81% and 94%.

The descriptive statistics of property price data for the period from 2010 to 2021 are shown in Table 1. The average sales price of a property was around €290,000 with a standard deviation of €190,000. Around 43% of the properties in the sample are terraced houses. Thus, terraced houses are the most common property type, followed by apartments (the reference category in our analysis) with around 27%. Detached and semi-detached properties are less common, each accounting for around 15% of total property transactions. We further have information on the state of maintenance, size, number of (bath)rooms, presence of a garden, parking, whether the property is listed as a monument, and the construction period.[3] Previous studies investigating this data (e.g. Koster and van Ommeren, 2015; Dröes and Koster, 2023) use a similar selection of variables. Particularly, the construction period is an important variable as it determines which properties are prone to foundation damages as a result of land subsidence. Indicatively, more than 62% were built before the 1980s, and these included many homes with shallow or

[3] Although the exact construction year is included in the data set, the variable is missing for 10% of observations. Hence, we use the construction period in our analysis.

Table 1: Descriptive statistics - property characteristics, 2010-2021

Statistic	Mean	St. Dev.	Min	Max
Price (€)	290,974	190,474	12,500	2,500,000
Size in m^2	122.846	50.848	25	2,400
Number of rooms	4.638	1.586	1	198
Number of bathrooms	0.900	0.509	0	8
Terraced property	0.428	0.495	0	1
Semi-detached property	0.154	0.361	0	1
Detached property	0.147	0.354	0	1
Property has garden	0.630	0.483	0	1
Property has garage	0.277	0.448	0	1
Property has central heating	0.938	0.241	0	1
Maintenance is good	0.858	0.350	0	1
Property is listed as monument	0.010	0.099	0	1
Constructed 1945-1959	0.080	0.272	0	1
Constructed 1960-1970	0.151	0.358	0	1
Constructed 1971-1980	0.162	0.369	0	1
Constructed 1981-1990	0.130	0.336	0	1
Constructed 1991-2000	0.131	0.337	0	1
Constructed after 2000	0.115	0.319	0	1

Note: This table shows housing transactions data from the Dutch Association of Realtors (NVM) provided by Brainbay. Observations: 1,441,391.

pole foundations.

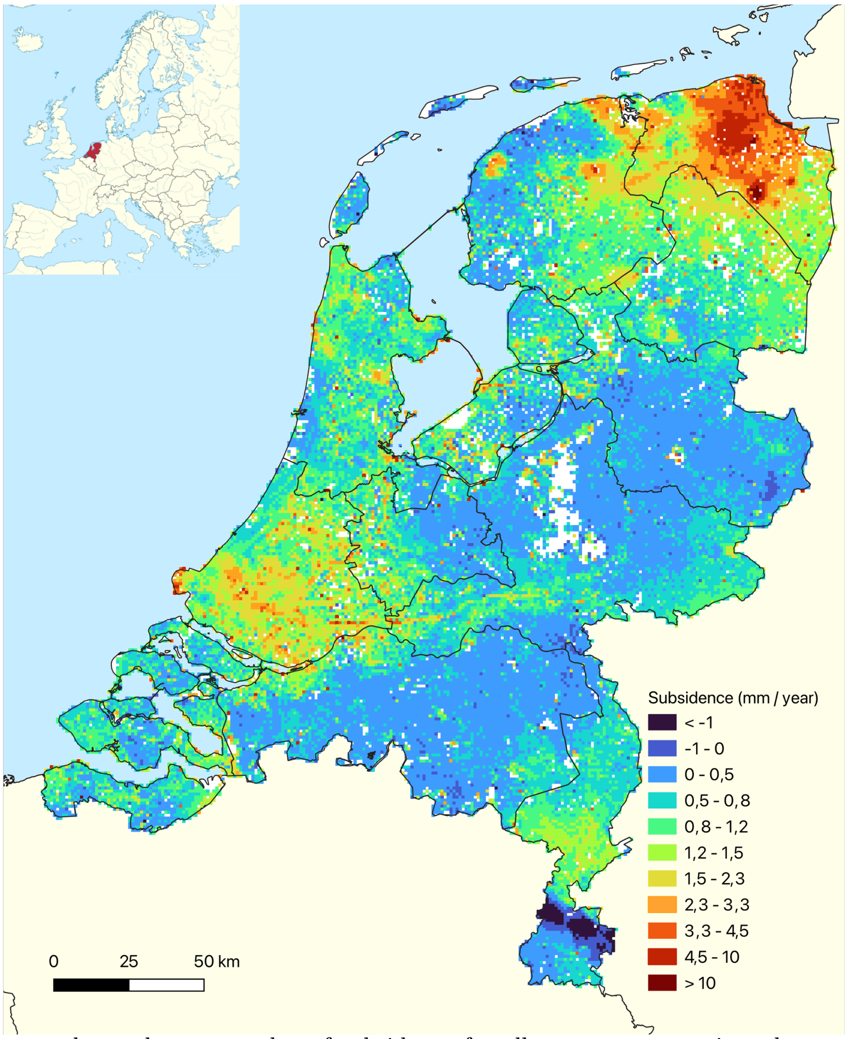
3.2 Climate Risks

3.2.1 Current Subsidence

Data on current subsidence rates is obtained from version 2.2 of the subsidence map (in Dutch: *bodemdalingskaart*) made by a consortium of universities, research centers, and geodetic companies in the Netherlands. The map is based on InSAR technology, applying satellite measurements from eight different positions. The elevation of a total of 305 million points is measured in 12-day intervals between October 2017 and October 2022. Based on these observations over the five-year period, a linear trend of yearly subsidence is provided in the data. To ensure the quality of the measurements and to reduce the dataset to a workable size, we drop all measurements which have a quality index of less than 0.8. A value of 0.8 or higher means good to very good quality. The measurement points have stable radar reflections over long periods of time, low noise, and consistent results. This restriction reduces the size of the dataset to 55 million measurement points for which a yearly trend is available.

In Figure 1, we show the spatial distribution of subsidence. The map shows that the most

Figure 1: Current subsidence



Note: The map shows the mean value of subsidence for all measurement points that are contained in grid cells of size 1000m × 1000m. This is an original visualisation based on version 2.2 of the subsidence map (*bodemdaalingskaart*).

affected area is the province of Groningen in the north-east of the Netherlands. This is not surprising as this is the area where gas extraction leads to increased subsidence as well as earthquakes. However, substantial variation remains outside Groningen, for example, in the provinces of Friesland and South Holland.

We match each property in our dataset to the five closest measurement points. The median closest measurement point has a distance of 5.6 metres from the property. For the furthest measurement point, the median distance is 15.3 metres. The furthest measurement point is two kilometres away, but those observations are clear outliers. In general, the five closest measurements have very similar values, with the median largest difference between points being 1 mm per year. The maximum difference is 3 cm per year.

From these five measurement points we compute a measure of property-level subsidence using inverse distance weighting according to the formula:

$$y = \sum_{i=1}^{5} \frac{d_i^{-p} x_i}{\sum_{j=1}^{5} d_j^{-p}}, \tag{1}$$

where x_i denotes the value at measurement point i, d_i refers to the distance of point i to the property and p is the power parameter that governs how fast the influence of a measurement point deteriorates with increasing distance. For the analysis, we choose a conventional parameter of $p = 2$ (Shepard, 1968).

Table 2: Descriptive statistics - climate risks, 2010-2021

Statistic	Mean	St. Dev.	Min	Max
Current subsidence (m)	0.001	0.001	−0.026	0.030
> 0 mm	0.871	0.335	0	1
> 3.3 mm	0.268	0.443	0	1
> 6.7 mm	0.013	0.112	0	1
Future subsidence (m)	0.040	0.098	0	1.104
> 0 cm	0.220	0.415	0	1
> 10 cm	0.102	0.303	0	1
> 20 cm	0.067	0.250	0	1
Floods 1/10 years	0.001	0.034	0	1
Inundation depth (m)	0.001	0.028	0	4.964
Floods 1/100 years	0.127	0.333	0	1
Inundation depth (m)	0.109	0.414	0	7.300
Floods 1/1,000 years	0.338	0.473	0	1
Inundation depth (m)	0.428	0.833	0	12.180
Floods 1/100,000 years	0.513	0.500	0	1
Inundation depth (m)	0.746	1.071	0	12.620
Search volume intensity	0.122	0.134	0	1
× current subsidence > 3.3 mm	0.033	0.088	0	1
× future subsidence > 10 cm	0.013	0.057	0	1
Search volume intensity (province adjusted)	0.031	0.049	0	1
× current subsidence > 3.3 mm	0.012	0.041	0	1
× future subsidence > 10 cm	0.003	0.019	0	1
Current subsidence × Built before 1980	0.170	0.376	0	1
Current subsidence × Floods 1/100,000 years	0.164	0.371	0	1
Future subsidence × Built before 1980	0.050	0.218	0	1
Future subsidence × Floods 1/100,000 years	0.076	0.265	0	1

Note: This table shows the descriptive statistics of current (historical) subsidence, future subsidence, and flood risk across houses in the Netherlands. The observations vary between 1,438,894 and 1,441,391.

Descriptive statistics of current subsidence at the property level are shown in Table 2. The average property is subsiding by just 1 mm per year. However, there is substantial variation across properties. The most affected properties are subsiding by as much as 3 cm per year. The elevation on some measurement points is actually rising. This could, for example, be caused by human activity such as soil restoration and waste disposal or by geologic factors such as tectonic activity (Murfin and Spiegel, 2020). This affects only a minority of properties as shown by the fact that 87.1% of properties are affected by a positive degree of soil subsidence. Furthermore, 26.8% of properties face a significant level of subsidence of more than 3.3 mm per year, a threshold we will use in our analysis. This threshold is in line with expert advice on foundation damages (Willemsen et al., 2020), but also corresponds to a 10 cm subsidence level over 30 years, which has been indicated in the literature as a threshold at which damage to a building starts to occur (Sundell et al., 2019), and it also corresponds to how future subsidence until 2050 is classified (see next section). We will also explore alternative thresholds such as 6.7 mm per year. Only 1.3% of properties are exposed to this type of severe subsidence level at which severe functional and structural damages start to become likely (Sundell et al., 2019).

3.2.2 Future Subsidence

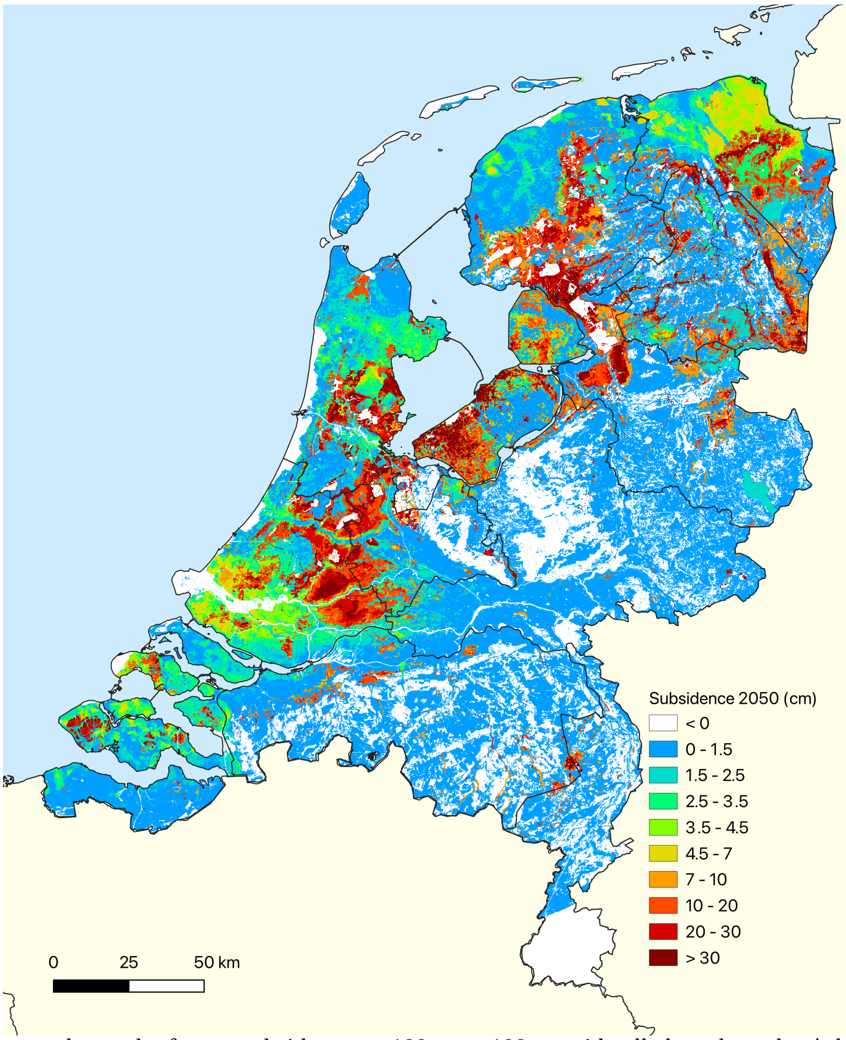
Data on predicted future subsidence and flood risks are based on maps developed by various knowledge institutions and consulting firms in coordination by the Climate Adaptation Services (CAS) foundation and commissioned by the Ministry of Infrastructure and Water Management (`www.klimaateffectatlas.nl`). The data has a resolution of 100 m × 100 m and we again match the data to the transactions data.

Forecasts of future subsidence are based on the Atlantis model described in Bootsma et al. (2020). Atlantis accounts for subsidence caused by consolidation, the compression of soil due to applied stress, and oxidation of organic soil layers (i.e. peat) above groundwater level. In Atlantis the entirety of the Netherlands is discretized in a grid of three-dimensional cells called voxels. For each voxel, the dataset stores the soil layers at depths between 0.5 m to 50 m below the surface. The values are derived from the GeoTOP dataset that outlines the soil composition in the entire Netherlands. A voxel covers a surface area of 100 m × 100 m, which corresponds to the resolution of GeoTOP. Multiple voxels form a water level management area (about 1,200 areas) and groundwater levels are uniformly set for each area.

A strength of the Atlantis model is that it explicitly models policy decisions as water management policy is a key determinant of soil subsidence. Furthermore, it allows for assumptions on the severity of climate change. The frequency of droughts can affect groundwater levels, while higher temperatures can speed up the oxidation of peat (Klimaateffectatlas, 2021).

Predictions of future subsidence based on the Atlantis model are for a high and a low scenario. The scenarios combine assumptions on the severity of climate change and the pursued water management policies. The high scenario assumes that the current policy of water level indexation is continued. Under water level indexation, the distance between surface and groundwater level is held constant. This is a prerequisite for productive use of the land in agriculture and construction, but also leads to further subsidence as the required lowering of the groundwater leads to further dehydration of soil. The low scenario, on the other hand, assumes water level fixation, which holds the groundwater fixed at the current level. This lowers the extent of subsidence, but renders the land unusable for agriculture. Therefore, the extensive implementation of water level fixation is unlikely, which is why we use the high scenario in the analysis. There is also a map until 2100 but we will use the 2020-2050 map as it is likely more accurate and a more relevant risk for a typical household.

Figure 2: Future subsidence, 2020-2050



Note: The map shows the future subsidence at 100 m × 100 m grid cells based on the Atlantis model (Bootsma et al., 2020). Data is obtained from the Climate Impact Atlas (*klimaateffectatlas*).

The spatial distribution of future subsidence is shown in Figure 2. The map shows that land subsidence will be most severe in North and South Holland, Friesland and Flevoland. The ground in these areas is to a large extent comprised of soft soils like peat and clay, which are prone to soil subsidence when dehydrated. Parts of these areas are located on polders, which are land areas reclaimed from the sea that are often subsiding over time due to ongoing dehydration.

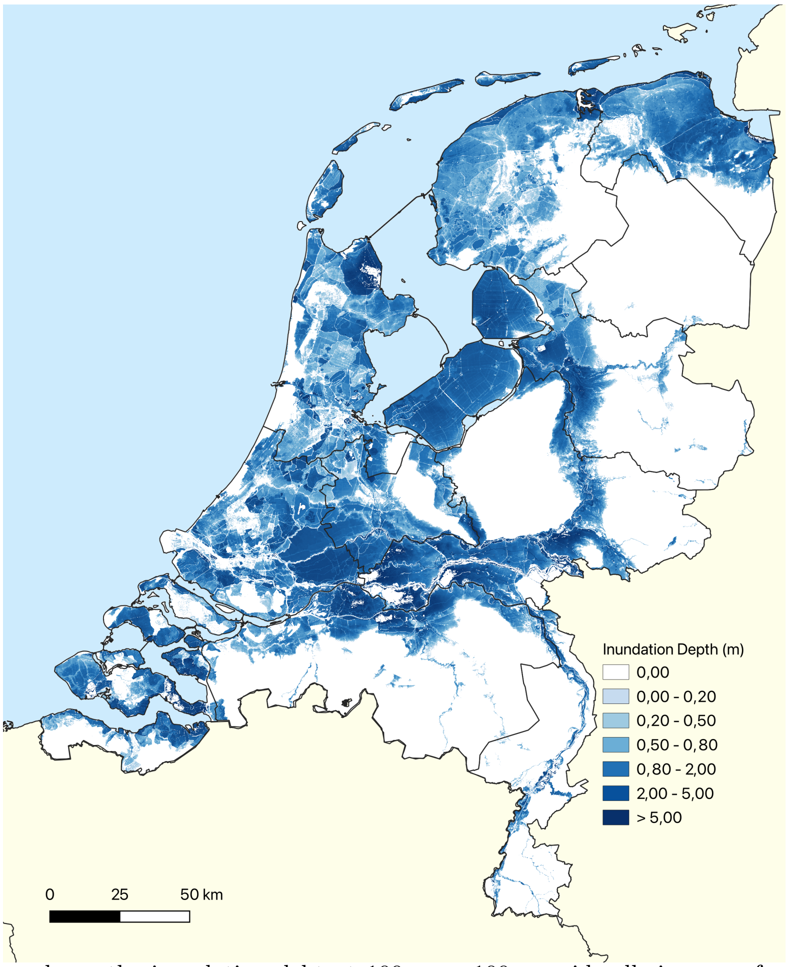
Comparing Figures 1 and 2, there appear to be differences between current and future subsidence. These differences relate to the extraction of natural gas, climate change, and policy choices in water level management. First, Groningen is currently a hot spot of subsidence due to the extraction of natural gas (Koster and van Ommeren, 2015). As gas extraction phases out, subsidence in the area might slow down in the long term (Klimaateffectatlas, 2021). Second, with the progression of climate change, temperatures and the frequency of droughts in the Netherlands are expected to increase. More frequent droughts will put pressure on groundwater levels, which will advance dehydration of soft soils, and higher temperatures accelerate the oxidation of peat (Klimaateffectatlas, 2021). Therefore, subsidence rates are likely to increase in areas with peat and clay soils. Finally, water management is an important determinant of subsidence rates (Bootsma et al., 2020). The response to climate change and progressing subsidence that authorities adopt can, therefore, cause differences between current and future subsidence; although radical changes in water management policy seem unlikely, as argued above (Klimaateffectatlas, 2021).

Descriptive statistics on the forecast of subsidence are presented in Table 2. The average property will subside by 4 cm until 2050. In extreme cases, the soil beneath a property could subside by as much as 1.1 metres. Negative subsidence and very small positive subsidence rates are not considered in the forecast. Until 2050, 22% of properties will experience some degree of soil subsidence. 10.2% of properties will subside more than 10 cm, which corresponds to the threshold applied in the baseline analysis. Finally, 6.7% of properties will experience extensive subsidence of more than 20 cm until 2050. As the correlation between current and future subsidence at a property level is only 0.12 there seems to be sufficient variation to measure both effects on property prices. A correlation matrix with flood risk, pole rot vulnerability, and differential settlement vulnerability is available in Appendix Table C.1.

3.2.3 Flood Risk

The flood risk maps show the inundation depth in case of a failure of the primary flood defenses. The probability of this failure depends on the local state of the flood defenses and varies across the country. Therefore, there are four versions of the map with different flood probabilities. Depending on the probability, a flood is expected once in 10 years, 100 years, 1,000 years, or 100,000 years, respectively. The maps are based on simulations of complex hydrological models conducted by the research company Deltares. As it is extremely unlikely that all flood defenses would fail simultaneously, not all areas indicated as being at risk of flooding in the map would inundate at the same time. Notably, the flood risk maps do not give a forward-looking account of flood risk, but instead reflect the *current* state. Therefore, information on future subsidence is not factored in, while current and realized subsidence is reflected in new versions of the maps.

Figure 3: Inundation depth, floods 1/100,000 years



Note: The map shows the inundation debt at 100 m × 100 m grid cells in case of a failure of the primary flood defenses, which is projected to occur once in 100,000 years. Data is obtained from the Climate Impact Atlas (*klimaateffectatlas*).

A map showing the inundation depths under the scenario with extremely small probability is shown in Figure 3. Maps for all four scenarios are shown in Appendix Figure B.2. For the main analysis, we create an indicator variable that is equal to one if the property is inundated in the event of a breach in the flood defenses that occurs once in 100,000 years. This corresponds to the measure that is used in the main analysis of Bosker et al. (2019) and compares properties that are exposed to some degree of flood risk to properties that are flood safe. Choosing one of the three other levels of flood risk compares properties at risk of flooding to properties that have a lower (or zero) probability of flooding. As buyers seem to overestimate very low probabilities of flooding (Bosker et al., 2019), a comparison between flood-prone and flood safe houses seems more clear-cut.

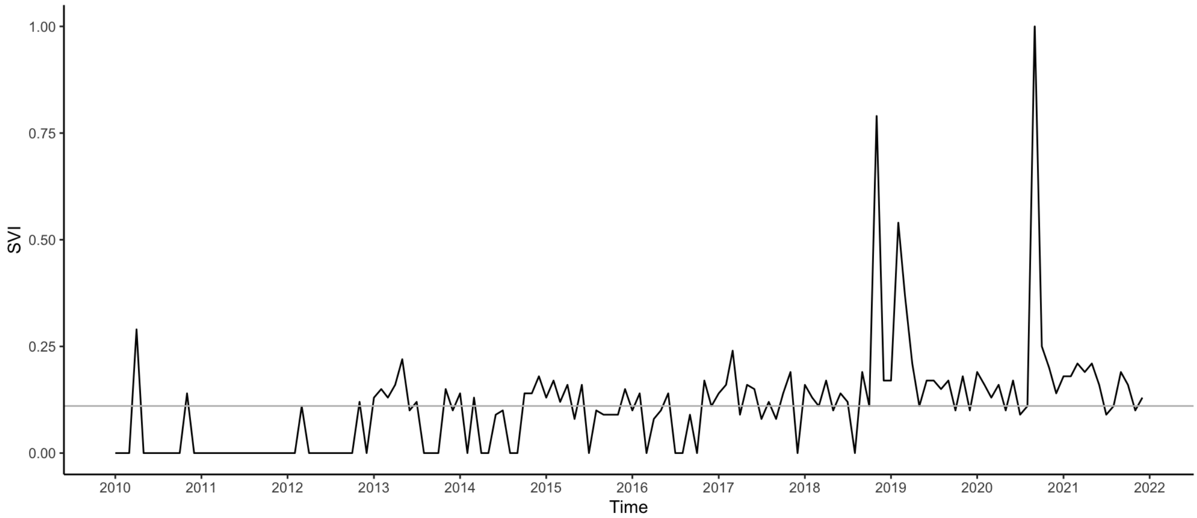
The descriptive statistics of different degrees of flood risk and the corresponding inundation depths are shown in Table 2. Only 0.1% of properties face a high flood risk, which corresponds to a flood being predicted roughly once every 10 years. These properties are located outside the dike rings, as those investigated by Niu et al. (2025). 12.7% of properties are expected to flood roughly once every 100 years. Around 33.8% of properties face a small flood risk, which predicts a flood once every 1,000 years. Considering the lowest level of flood risk under which a flood is expected only once in 100,000 years, 51.3% of properties in the sample are at risk of flooding. The maximum inundation depth under a high likelihood of flooding is 4.9 metres. When looking at the lowest chance of flooding, the maximum inundation depth increases to 12.6 metres.

3.3 Attention to Subsidence

Following Da et al. (2011) and Choi et al. (2020) we measure salience using the search volume intensity (SVI) of Google queries related to land subsidence. In addition to yielding information on potential mechanisms, temporal variation in SVI provides a potential source of exogenous variation that can be exploited for causal identification (Giglio et al., 2021a). Specifically, we construct a time series with monthly observations of SVI for the search term (in Dutch) ‘land subsidence’. Google Trends reports observations relative to the time period with the highest SVI. Thus, a value of 1 corresponds to the month with the maximum number of searches. For ease of interpretation of the empirical results, we transform the variable so that a value of 0 corresponds to the mean level of SVI and 1 corresponds to one standard deviation above the mean.

The time series variation in SVI is shown in Figure 4. The time series exhibits significant month-to-month variation. In the early years of the sample, observations with a relative SVI of zero are frequent. Starting around 2013, most observations in the sample remain relatively close to the mean of 0.13. SVI is the largest in months when new information on subsidence became available. The first version of the current land subsidence map was released in November 2018 and version two was published in September 2020. SVI clearly spikes around the availability of new subsidence maps, which indicates that market participants seem to take note of the information, at least momentarily.

Figure 4: Search volume intensity



*Note:*The figure is based on Google trends data of households looking for land subsidence (in Dutch: 'bodemdaling'). The current subsidence map and its update were introduced in November 2018 and September 2020, respectively.

In addition to the time-series variation, Google Trends provides spatial variation of SVI. For the Netherlands, this variation is provided at the province level. Appendix Figure B.3 shows relative SVI at the province level. Unsurprisingly, SVI is the highest in the province of Groningen, where the extraction of natural gas caused large subsidence rates and even earthquakes. Groningen is followed by the neighbouring provinces of Drenthe and Friesland, which are also partially affected by earthquakes and subsidence resulting from the gas extraction. Other provinces with larger salience are Utrecht, South Holland, and Flevoland, where subsidence related to agriculture is relatively important. Overall, there seems to be substantial temporal and spatial variation in the amount of attention individuals in the Netherlands pay to land subsidence.

4 Empirical Design

To estimate the effect of subsidence on property prices, we use a hedonic pricing model. Several studies (Bosker et al., 2019; Murfin and Spiegel, 2020; Giglio et al., 2021b) have applied hedonic pricing to estimate the impact of climate risks on property prices. A potential concern when estimating the impact of soil subsidence on property prices is omitted variable bias due to unobserved local characteristics that affect both the occurrence of subsidence and property prices. One of these characteristics could, for instance, be related to the local importance of agriculture. As dehydration of soft soils for agriculture is the main driver of subsidence in the Netherlands (Bucx et al., 2015), subsidence might be more likely to occur in rural areas that face lower property prices than urban centers. Groundwater levels themselves are another example. Groundwater levels directly drive subsidence and there is local variation among the levels that are adopted (Bootsma et al., 2020). Another possible characteristic could be the type of soil. Subsidence is more likely to occur on peat and clay grounds, which frequently occur in the provinces of North and South Holland. As the most populous cities of the Netherlands are located within these provinces, it is likely that properties in these areas obtain higher prices.

To address this challenge, we apply a border discontinuity design (BD), see Black (1999). To illustrate the idea behind the identification strategy, consider the equation for (log) property prices p from Gibbons et al. (2013):

$$p = s(c)\beta + x(c)\gamma + g(c) + \varepsilon \tag{2}$$

where $x(c)$ denotes characteristics of a property at location c. Furthermore, $s(c)$ denotes the variable of interest, $g(c)$ captures unobserved local determinants of market prices, and ε refers to the error term. Under the assumption that the unobserved local characteristics $g(c)$ are continuous in location c, they can be eliminated by taking differences between two properties i and j that are located in close proximity:

$$(p_i - p_j) = (s(c_i) - s(c_j))\beta + (x(c_i) - x(c_j))\gamma + g(c_i) - g(c_j) + (\varepsilon_i - \varepsilon_j) \tag{3}$$

To consistently estimate effects, $g(c_i) - g(c_j)$ needs to be effectively random and uncorrelated to $s(c_i) - s(c_j)$. These conditions hold approximately when $s(c)$ is discontinuous between two close locations, while the function $g(c)$ remains continuous. The BD approach exploits this by comparing properties on two sides of a boundary, which marks a discontinuity in $s(c)$. Following this approach, we compare properties that are significantly affected (subsidence > 3.3 mm per year) by subsidence to nearby properties that are less affected. To test the sensitivity of the results to this cutoff, we present additional estimates using cutoffs of 0 mm per year and 6.7 mm per year, respectively.

In the original work by Black (1999) and subsequent studies, applying BD only observations within a close distance to the border are included in the regression. That is, observations falling within the distance threshold are weighted with factor one, while observations further away are weighted with factor zero. Therefore, defining the distance threshold is an important decision made by the researchers. However, there is no clear guidance on which threshold to choose. Gibbons et al. (2013) refine BD by weighting each observation by the inverse distance to the boundary. This implies that properties close to the boundary receive the highest weight, and that weights gradually diminish with increasing distance. The distribution of distances to the border is shown in Appendix Figure B.4. The majority of observed transactions are located within 100 m of a property with a different exposure to land subsidence. Consequently, properties in close proximity to properties with a differing exposure to subsidence have the largest impact on the estimation of effects.[4] In Appendix Table C.2, we demonstrate that the results are not sensitive to weighting observations by the inverse distance to the boundary by repeating the main analysis only for properties within a specific distance of properties with a different degree of soil subsidence.

Formally, we estimate the following equation:

$$\begin{aligned} p_{it} = {} & cs_i\alpha_1 + fs_i\alpha_2 + flood_i\alpha_3 + cs_i \times b1980_i\alpha_4 + fs_i \times b1980_i\alpha_5 \\ & + cs_i \times flood_i\alpha_6 + fs_i \times flood_i\alpha_7 + X_i'\beta + \lambda_j + \lambda_t + f(distance_i) + \varepsilon_{it} \quad (4) \end{aligned}$$

where p_{it} denotes the log transaction price of property i sold at time t, current subsidence is denoted cs, future subsidence is denoted fs, $flood$ captures if the property would flood if the primary flood defenses would fail, $b1980$ is an indicator variable that equals one if the property was constructed before (or at) 1980, X is a vector of hedonic property characteristics (i.e., the size of the property, the number of rooms and bathrooms, the type of the property, whether the property has a garden, garage and central heating, the state of maintenance, whether the property is listed as a monument, and six construction period dummies), λ_j captures 4-digit zip-code fixed effects, and λ_t refers to month and year fixed effects. Finally, $f(distance_i)$ denotes a function of the distance of property i to the boundary. We include up to third order polynomials

[4] It is relatively straightforward to think of current subsidence in a BD framework as the variable is measured at the property level. However, other variables such as future subsidence and flood risk only vary at a grid of 100 m × 100 m. As the boundary is unlikely to correspond with the edge of the grid cell, there is a distance band of 100 m around the boundary for which these variables are identical. Identifying variation for these variables will, therefore, come from properties located in the next grid cell. This might lead to an underestimation of effects as observations further away from the boundary receive lower weights.

of the distance to the border.[5] With the inclusion of these distance polynomials, we control for spatial trends in amenities that differ across the border (Gibbons et al., 2013).[6]

There are several identification challenges in estimating Eq. (4). As mentioned, until the mid 1970s, properties were built on foundations that were susceptible to damage. Properties constructed later are likely to have a concrete foundation that is not prone to damage. As the change in the use of foundation type falls within the construction period 1971-1980, we define properties built up to this period as most at risk for our main analysis (the variable $b1980$). This might lead to a conservative estimate of the effect of current and future land subsidence as some properties might already have had a concrete foundation during the 1971-1980 period. Therefore, we also estimate the regression using 1970 as an alternative threshold. As there might be some properties built before the 1970s that use concrete foundations, we might still conservatively estimate the effect of land subsidence, but we would expect the impact of this selection to be small as concrete foundations were more of the exception than the rule. Similarly, after the 1980s, it is still possible yet very unlikely that properties do not have a concrete foundation. If this would be the case, however, it could potentially lead to an overestimation. Also, although it is possible to change the foundation from shallow or wooden pole to modern concrete, it is a complex, expensive, and invasive process. It is usually only done when there is actual foundation damage (and particularly after the 1980s). However, if changes or repairs are made to the foundation, some of the properties at risk might no longer be at risk, again leading to a conservative estimate.

The regression in Eq. (4) aims to identify the direct and indirect effects of land subsidence on properties. The inclusion of current and future subsidence captures their effect that is common to all properties irrespective of risk exposure. The interaction terms between subsidence and the 1980 dummy aim to capture the direct foundation damages caused by subsidence. These damages mainly affect properties with pole and shallow foundations but not properties with concrete foundations. Most properties constructed after the 1970s possess concrete foundations. Finding a significant interaction term would, therefore, indicate that properties that are more prone to foundation damage are affected differently by subsidence. Interacting subsidence with

[5]For properties affected by subsidence we include first, second and third order polynomials of the distance to the nearest property, which is less affected by subsidence. For properties not subsiding or subsiding at a low rate, we include the corresponding polynomials of the distance to the nearest property, which is significantly affected by subsidence.

[6]This could for example be the case in the gas fields in Groningen, where the extraction of natural gas causes subsidence. If households experience disamenities from living near extraction facilities, prices would be expected to fall with increasing distance to the nearest property that is unaffected.

the flood risk status of a property identifies the indirect effects of subsidence due to increased vulnerability to flooding. Finding a significantly negative interaction term indicates that market participants anticipate increases in potential flood damages due to the impact of subsidence.

5 Results

5.1 Baseline Results

The estimation results of Eq. (4) are shown in Table 3. In Column 1, we only include indicator variables of current subsidence above 3.3 mm per year and future subsidence of more than 10 cm between 2020 and 2050, along with year, month, and four-digit postcode fixed effects. The coefficient for current subsidence is statistically significant at the 5% confidence level and suggests that properties currently affected by subsidence trade at a discount of around 0.5%. The coefficient of future subsidence is statistically indistinguishable from zero.

In Column 2, we add property characteristics. The coefficient of current subsidence slightly increases now, suggesting a 0.35% discount. The coefficient of future subsidence becomes negative and statistically significant at the 1% level. Properties projected to significantly subside until 2050 trade at a discount of 1.3%. This large shift indicates that properties located in areas affected by future subsidence possess desirable observable characteristics so that a negative effect only appears after controlling for these characteristics.

The coefficients of property characteristics (not shown in Table 3) offer few surprises. Larger properties and properties with more rooms are more expensive. So are properties with a garden, garage, central heating, a good maintenance state, and monument status. The prices of detached and semi-detached houses are higher than the prices of terraced houses and apartments. Finally, houses built after 1990 are more expensive than houses built before.

Column 3 adds distance polynomials. For properties exposed to subsidence levels of more than 3.3 mm per year, we include a linear, quadratic, and cubic term of the distance to the nearest property facing subsidence of less than 3.3 mm per year. Similarly, we include the three polynomials of distance to the nearest property facing subsidence levels of more than 3.3 mm, if the property is exposed to lower levels of subsidence. Compared to Column 2, the estimates remain virtually unchanged.

In Column 4, we differentiate the effect of subsidence between properties constructed before and after 1980. Properties constructed after 1980 are built on concrete foundations, which are not prone to foundation damage. Properties constructed before 1980 are likely to have a pole or shallow foundation, which can sustain damages when exposed to soil subsidence. Therefore, we expect *direct* effects of soil subsidence to be concentrated among properties constructed before 1980. This is exactly what we observe for current soil subsidence. The coefficient on subsidence becomes statistically insignificant. Instead, the coefficient on the interaction term is significant at the 1% level and suggests that older properties exposed to soil subsidence obtain 0.8% lower prices than comparable properties not exposed to soil subsidence. This is not the case for future soil subsidence. The coefficient for this variable increases slightly. The point estimate of the interaction term is not statistically significant.

The model in Column 5 additionally controls for flood risk. The point estimate is negative but not statistically significant. The remaining coefficients are almost identical to the ones obtained under the previous specification.

Finally, Column 6 shows estimation results for the full model specification. This specification includes interaction terms between subsidence and flood risk to identify *indirect* effects of subsidence that affect property prices through a change in flood risk exposure. The interaction term between flood risk and current subsidence is positive, small and statistically insignificant. If flood risk maps are updated frequently, they should account for information on historic and current subsidence. Therefore, the effect of subsidence is already included in the flood risk measure, which explains the statistically insignificant interaction effect. For future subsidence, however, the interaction term is negative and statistically significant. A property that is affected by both future land subsidence and flood risk trades at a discount of 1.5%. The coefficient of future subsidence is no longer statistically significant and less negative. This suggests that the significant estimate in the previous specifications was driven by houses exposed to future subsidence and at risk of flooding.

In our main specification we use the log transaction price as the dependent variable. In Appendix Table C.3, we present additional results using the log asking price and log time on market as dependent variables. For the asking price, the point estimate of the interaction between current subsidence and exposure to foundation risk is smaller in magnitude, while the interaction between future subsidence and flood risk is slightly larger. However, both point estimates are within the 95% confidence intervals from our baseline estimation. When looking at time on market, we find that properties exposed to flood risk sell more quickly. In contrast, subsidence does not affect the time on market.

Table 3: Baseline results

	Log price					
	(1)	(2)	(3)	(4)	(5)	(6)
Current subsidence > 3.3mm	-0.0049**	-0.0034***	-0.0031**	0.0016	0.0017	0.0005
	(0.0019)	(0.0012)	(0.0013)	(0.0018)	(0.0018)	(0.0024)
Future subsidence > 10cm	0.0002	-0.0127***	-0.0128***	-0.0162***	-0.0158***	-0.0047
	(0.0127)	(0.0046)	(0.0046)	(0.0046)	(0.0046)	(0.0068)
Current subsidence > 3.3mm × Built before 1980				-0.0080***	-0.0080***	-0.0080***
				(0.0022)	(0.0022)	(0.0022)
Future subsidence > 10cm × Built before 1980				0.0062	0.0059	0.0053
				(0.0075)	(0.0075)	(0.0074)
Floods 1/100,000 years					-0.0087	-0.0077
					(0.0058)	(0.0062)
Current subsidence > 3.3mm × Floods 1/100,000 years						0.0019
						(0.0024)
Future subsidence > 10cm × Floods 1/100,000 years						-0.0152**
						(0.0074)
Observations	1,441,248	1,440,339	1,440,339	1,440,339	1,437,985	1,437,985
R^2	0.51842	0.85451	0.85461	0.85463	0.85435	0.85437
Within R^2	0.00004	0.69751	0.69773	0.69776	0.69764	0.69767
Year, Month and 4PPC fixed effects	✓	✓	✓	✓	✓	✓
Property characteristics		✓	✓	✓	✓	✓
Distance polynomials			✓	✓	✓	✓

Note: Standard errors are clustered at the 3PPC level. Observations are weighted by the inverse distance to the boundary between properties exposed to current subsidence and unaffected properties. The regression in Column 1 estimates the effect of current and future subsidence including year, month, and four-digit zip-code fixed effects. In Column 2 we add hedonic characteristics. Column 3 adds first, second, and third order polynomials of the distance to the nearest property with a differing exposure to current subsidence. In Column 4 we allow the effects of subsidence to differ for properties that are more likely to have a weak foundation (constructed before 1980). In Column 5 we add exposure to flood risk. Our full specification in Column 6 allows the effect of flood risk to differ between flood-safe and flood-prone properties. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

We perform several robustness checks. A detailed exposition is given in Appendix A. In particular, we use a property at risk cut-off year of 1970, investigate whether the effect of subsidence differs by inundation depth, and change the weighting and distance cut-offs to the boundary of the borders. We further show results approximating repeat sales and regressions controlling for local trends, and use alternative definitions of the subsidence variables (thresholds and differential subsidence). Finally, we explore the definition of flood risk (i.e., expected occurrence every 100 or 1000 years) and show some subsample analyses (e.g., excluding earthquake areas, the 2021 major flood event, rising land areas in Limburg). Our results are particularly robust to these changes and additions.

5.2 Salience of Subsidence

To understand the mechanism behind the price effects identified in the previous section, we test how the salience of land subsidence among the Dutch population affects our estimates. To measure salience, we rely on search volume intensity (SVI) for the term land subsidence (in Dutch) provided by Google Trends. Several studies (Choi et al., 2020; Giglio et al., 2021b; Ling et al., 2024) explore how the pricing of climate risks changes with the salience of the risk. Climate risk is usually slow-moving and the salience of the risk provides a convenient source of exogenous variation (Giglio et al., 2021a).

The use of Google Trends data to measure attention is well established in the literature. Da et al. (2011) use the SVI of stock tickers to measure investor attention. Choi et al. (2020) show that searches related to climate change increase in times with abnormally warm weather and that stocks of carbon-intensive firms trade at a discount during these times. Commonly, there are two potential challenges to the use of Google Trends data. First, for some terms (e.g. "Apple"), the intent behind the search is ambiguous (Da et al., 2011). Second, different terms can refer to the same concept. In these cases, it might be difficult to decide which term should be used (Choi et al., 2020). Both of these problems seem to be less of a concern in our application. *Land subsidence* as a term clearly refers to the sinking of the land surface and is the most frequently used term in communication about the topic (Klimaateffectatlas, 2021).

To analyse the impact of salience, we consider the temporal and spatial variation in SVI outlined in Section 3.3. Specifically, we multiply the indicator variables for current and future subsidence by SVI in a property's transaction months.[7] We add these variables and all their

[7] We also use average SVI in the months prior to the transaction. The results remain unchanged.

Table 4: Search volume intensity

	Log price		
	(1)	(2)	(3)
Current subsidence > 3.3mm	0.0005	0.0015	-0.0000004
	(0.0024)	(0.0025)	(0.0025)
Future subsidence > 10cm	-0.0047	-0.0037	-0.0045
	(0.0068)	(0.0070)	(0.0068)
Floods 1/100,000 years	-0.0077	-0.0076	-0.0073
	(0.0062)	(0.0062)	(0.0062)
Current subsidence > 3.3mm × Built before 1980	-0.0080***	-0.0086***	-0.0079***
	(0.0022)	(0.0022)	(0.0022)
Future subsidence > 10cm × Built before 1980	0.0053	0.0048	0.0052
	(0.0074)	(0.0078)	(0.0072)
Current subsidence > 3.3mm × Floods 1/100,000 years	0.0019	0.0008	0.0026
	(0.0024)	(0.0025)	(0.0024)
Future subsidence > 10cm × Floods 1/100,000 years	-0.0152**	-0.0165**	-0.0150**
	(0.0074)	(0.0075)	(0.0072)
Current subsidence > 3.3mm (SVI adjusted)		-0.0081***	-0.0106***
		(0.0019)	(0.0025)
Future subsidence > 10cm (SVI adjusted)		-0.0063	-0.0094
		(0.0051)	(0.0057)
Current subsidence > 3.3mm (SVI adjusted) × Built before 1980		0.0059***	0.0007
		(0.0015)	(0.0030)
Future subsidence > 10cm (SVI adjusted) × Built before 1980		0.0033	-0.0011
		(0.0061)	(0.0077)
Current subsidence > 3.3mm (SVI adjusted) × Floods 1/100,000 years		0.0096***	0.0140***
		(0.0023)	(0.0025)
Future subsidence > 10cm (SVI adjusted) × Floods 1/100,000 years		0.0098**	0.0133**
		(0.0043)	(0.0059)
Observations	1,437,985	1,437,985	1,437,985
R^2	0.85437	0.85445	0.85444
Within R^2	0.69767	0.69784	0.69781
Year, Month and 4PPC fixed effects	✓	✓	✓
Property characteristics	✓	✓	✓
Distance polynomials	✓	✓	✓
SVI province adjusted			✓

Note: Standard errors are clustered at the 3PPC level. Column 1 shows the results of our preferred specification from Column 6 of Table 3. In Column 2, we add subsidence variables that are adjusted for temporal variation in search volume intensity (SVI) of the term land subsidence. In Column 3, we account for temporal and spatial variation in SVI. ***p <0.01, **p <0.05, *p <0.1

relevant interaction terms to the regression specified in Eq. (4). A unit increase in SVI corresponds to an increase by one standard deviation. In the first specification, we only consider temporal variation. Subsequently, we also account for spatial variation in the SVI measure by including the relative SVI of the province in which the property is located.

Table 4 reports the results of estimations including SVI. Column 1 reports baseline estimates from Column 6 of Table 3 for reference. In Column 2, we add measures of current and future subsidence, which are adjusted with SVI. Compared to the baseline specification, coefficients of the direct and indirect effect of subsidence increase slightly. The effect of SVI adjusted current subsidence is negative and statistically significant. The coefficient suggests that a one standard deviation increase in the relative search frequency decreases the transaction price of all properties, which subside more than 3.3 mm per year by about 0.8%. This decrease is comparable in magnitude to the baseline effect of current subsidence for properties constructed before 1980, which underlines the importance of salience. Interestingly, this effect seems to be smaller for properties exposed to current subsidence, which were constructed before 1980 or that are at risk of flooding. Similarly, the effect is smaller for properties predicted to subside in the future, which are located in current flood zones. The respective interaction terms for these groups are positive and in the case of flood-prone properties large enough to outweigh the negative effect of salience. The estimates suggest that increased attention to subsidence decreases the price of properties that are currently subsiding. This effect, however, seems to be weakened or even reversed for the properties most at risk - those with a potentially weak foundation or an exposure to flood risk.

Column 3 shows how the estimates change when we account for spatial variation in SVI, next to the temporal variation. We do so by multiplying the relative SVI in each month by the relative SVI of the province in which the property is located. Relative SVI at the province level is shown in Figure B.3. Coefficients of direct and indirect effects are the same as in the baseline specification. Compared to the estimates from Column 2, the effect size of SVI adjusted current subsidence increases. A one standard deviation increase in SVI reduces the price of properties affected by current subsidence by slightly more than 1%. The interaction effect between current and future subsidence and flood risk remains positive and significant and increases slightly compared to the previous specification. The interaction term between current subsidence and a damage prone foundation is now close to zero and no longer significant, which indicates that the previous positive effect was driven by properties in provinces with lower SVI. This suggests that buyers who purchase a property in a province, where subsidence is not very salient do not consider foundation risk, even if they purchase a property, which is likely to have a damage-prone foundation and that is currently exposed to significant land subsidence.

The estimates in Table 4 reveal three key findings. First, salience as proxied by the frequency of Google searches clearly matters for the pricing of subsidence. During months with high degrees of salience, properties exposed to subsidence trade at a large discount. A one standard deviation increase in the volume of Google searches is associated with a price decrease of 0.8% to

1%. Second, spatial variation in salience impacts price effects. In provinces where subsidence is less salient, properties at risk of foundation damage seem to not trade at a discount when salience increases. A possible explanation is that buyers are simply less aware due to lower salience. Alternatively, buyers could generally be aware of the risk salience poses but wrongly assume that it does not pose a threat in their province, as coverage of subsidence might focus on the most affected areas such as Groningen. Third, an increase in salience implies a larger discount for properties that are affected by the direct effects of subsidence but not for properties impacted by the indirect effects. This could indicate that there are two groups of market participants who price subsidence risks. One group prices associated risks irrespective of the degree of salience, and another group is only aware of the risk when salience is high. Furthermore, the latter group only seems to consider the impact of subsidence on the foundation of a property while not connecting subsidence and flood risk.

6 Implications

6.1 Total Loss in Housing Values

To quantify the total reduction in property values caused by subsidence, we compute counterfactual prices without the impact of subsidence and multiply these by effect sizes, if the property is affected by subsidence. The figures are adjusted to 2021 prices, using the consumer price index figures of Statistics Netherlands (*Centraal Bureau voor de Statistiek, CBS*).

The results of this rough estimation suggest that between 2010 and 2021 around €545 million of housing wealth was lost due to *direct* foundation effects of subsidence. A further €518 million was lost to *indirect* effects, which lower the value of a house through increased vulnerability to flood risk. In total, subsidence caused price reductions of about €1.06 billion.

The sample contains about 1,4 million property transactions, which is about 18% of the total Dutch housing stock of 8 million properties (Dröes and Koster, 2023). Hans et al. (2024) show that, in terms of flood risk exposure, transactions are representative for the stock of properties as covered in the land registry. Assuming that subsidence is comparable between transactions and stock as well, the estimates suggest that subsidence causes an overall reduction of property prices of €5.89 billion (against a GDP of €856 billion in 2021 and a total transaction volume of €419 billion between 2010 and 2021).

The loss in housing wealth is comparable to the external costs of renewable energy production: the value lost due to the installation of wind turbines is €5 billion and the total loss related to solar farms is another €800 million (Dröes and Koster, 2021). Although wind turbines and solar farms have a larger effect on the individual property (1.8% and 2.6% respectively), the total costs are comparable. This suggests that subsidence affects a larger share of properties than the placement of wind turbines and solar farms. The estimated value reductions are larger than the non-monetary costs of earthquakes in Groningen, which are estimated to be €169 million (Koster and van Ommeren, 2015). They are also larger than the €1.2 billion of public investments for the compensation of inhabitants of the region affected by earthquakes (Koster and van Ommeren, 2015).

6.2 Perception of Climate Risks

To investigate whether the effects estimated in Section 5.1 reflect a rational capitalisation of foundation risk, we identify the expected probability of foundation damage that is consistent with the price effects. Under the assumption that the foundation damage occurs immediately after the purchase of the property, the effect size α should equal the expected probability of foundation damages p multiplied by expected damages $E[d]$:

$$\alpha = p \times E[d] \tag{5}$$

The coefficient of current subsidence for older properties at risk of foundation damages from Table 3 is -0.008, which suggests a price discount of around 0.8%. The mean house price in the sample is €290,000, which implies that being affected by subsidence and having a foundation that is prone to foundation risk, would lower the transaction price of the average property by €2,320. This price reduction is comparable to the cost of an additional area of 1.6 m^2, which corresponds to 1.5% of the area of the average house, or to 25% of the cost of an additional room. In many cases of foundation damage repair costs will be below €10,000 (Kok and Angelova, 2020). In more severe cases repairing a damaged foundation costs between €50,000 and €100,000 (Hommes et al., 2023). This implies that market participants expect a severely damaged foundation with a probability between 2.32% and 4.64% if the property is exposed to subsidence and built before 1980. Minor damages are expected with probability 23.2%. Results of this rough calculation are shown in Table 5.

These estimates seem to underestimate the actual risk of foundation damages. There are

Table 5: Inferred expected probabilities, land subsidence

Expected damage	€10,000	€50,000	€100,000
Expected probability	23.20%	4.64%	2.32%
Years to damage			
Discount rate			
2.5%	57	126	153
5%	28	62	76
7.5%	18	41	50

Note: This table shows the individual expectation that are implied by the result of our preferred specification from Column 6 of Table 3. For different values of expected (foundation) damage, we consider the case of an uncertain foundation damage immediately after the purchase as well as a certain foundation damage in the future under varying discount rates.

about 8 million homes in the Netherlands (Dröes and Koster, 2023) and about one million of them might be affected by foundation damage (Hommes et al., 2023). This would suggest a probability of being affected by foundation damage of roughly 17%, which coincidentally corresponds to the sample share of properties with a construction date before 1980 exposed to current subsidence of more than 3.3 mm per year (shown in Table 2). This price discount only applies to the properties *most* at risk (i.e. those affected by subsidence and constructed before concrete foundations were used). As it could very well be the case that the majority of exposed properties sustains foundation damages, even the implied probability of 23.2% for expecting minor damage to the foundation seems very optimistic. Furthermore, market participants seem to expect severe foundation damages only in 2.32%-4.64% of the cases. As full restoration might be necessary for up to 9% of properties (Kok et al., 2021), these expectations provide a further indication that the risk of foundation damages is underestimated.

A potential explanation for this underestimation is that market participants might expect financial support from the government. Currently, the homeowner has to pay for repairing a broken foundation and these costs are not insurable (Hommes et al., 2023). There is an ongoing policy discussion about the extent to which water management authorities should be liable for foundation damages and how government support can be extended to homeowners.[8] As the extent to which the government provides financial support in case of foundation damage remains unclear, it seems unlikely that market participants in the period from 2010 to 2021 were expecting government support. Instead, it seems more plausible that the underestimation

[8] See for instance the communications of the Union of Water Boards (https://unievanwaterschappen.nl/tweede-kamer-spreekt-met-waterschappen-over-funderingsschade/ and https://unievanwaterschappen.nl/sturende-rol-water-moet-verdere-funderingsschade-beperken/.

is caused by a lack of awareness. This is consistent with estimates suggesting that 85% of buyers are not aware of potential foundation risk (Bani et al., 2024). Thus, the results highlight that standardised disclosure of climate risks can help market participants to make informed decisions. As suggested by Bani et al. (2024), this disclosure could take the form of a climate label that highlights the risk exposure of a property.

Alternatively, one could think of a certain foundation damage occurring t years in the future.[9] Because the damage only occurs in the future it has to be discounted at discount rate β:

$$\alpha = (1 - \beta)^t \times E[d] \tag{6}$$

Giglio et al. (2015) estimate that the appropriate discount rate to choose for real estate cash flows 100 years or more in the future is 2.6%. We perform calculations using a discount rate of 2.5%. We also apply two larger discount rates, 5% and 7.5% respectively. The results are shown in Table 5. Depending on the discount rate and expected damages, foundation damages are expected to occur within 18 years for minor damages or within 41 to 153 years for severe damages.

Similarly, it is possible to investigate the magnitude of the effects found for the indirect effects of subsidence. In the main specification, we investigate the impact of future subsidence on properties already exposed to flood risk today. Thus, the risk of flooding will be unchanged. What will change in response to future subsidence is the expected damage in the event of flooding. This is due to the fact that subsidence leads to higher inundation levels, which are commonly associated with higher flood damages (Endendijk et al., 2023). Therefore, the effect should reflect the probability of a flood event multiplied by the expected change in damages due to subsidence:

$$\alpha = p \times \Delta E[d] \tag{7}$$

The effect is expressed as a percentage discount on the transaction. Accordingly, expected damages can be expressed in terms of damage to value. In this case, both p and $\Delta E[d]$ are bounded by one, as a flood cannot destroy more than the entire value of the property. The lowest expected probability that is consistent with these findings is a flood probability of 1.5%, which

[9] In reality, foundation damages will neither occur immediately after the purchase nor with certainty at a specific date in the future. Instead, there is a probability for the damage to occur in every year after the purchase. The results of these estimations can, therefore, be thought of as upper bounds for the expected probability of a foundation damage and the expected duration for damage to occur.

is significantly higher than the objective probability of 0.001%. A subjective flood probability of 1.5% would require that subsidence increases expected flood damages from 0% to 100%. Furthermore, these 1.5% are a lower bound as the calculation assumes a discount rate of 0. Therefore, the real expected probability will likely be significantly higher than 1.5%.

7 Conclusion

Combining detailed transaction data and granular data on current and future subsidence as well as flood risk, we show that there are significant *direct* and *indirect* price effects of land subsidence in the Dutch residential real estate market. Properties that rest on damage-prone foundations and are exposed to current subsidence trade at a price discount of 0.8%. Flood-prone properties that are predicted to experience subsidence in the future obtain prices that are lower by 1.5%. Our results complement earlier work by Murfin and Spiegel (2020) who study historical trends in relative sea level rise (RSLR), which largely reflect differences in vertical land motion. While Murfin and Spiegel (2020) find that RSLR is not priced, we investigate subsidence using direct satellite data and in a different country which is particularly prone to both flooding and subsidence. We find that the interaction between subsidence, foundation risk, and flood risk is particularly important to understand the impact on property prices.

Imputed expectations suggest that buyers underestimate the risk of foundation damages. Although the effect sizes are conditional on the property belonging to the most vulnerable group, buyers expect minor foundation damages with a probability of 23.2% and major damages with a probability between 2.3% and 4.6%. At the same time, it is estimated that 17% of all private properties will be affected by some form of foundation damage in the future (Hommes et al., 2023). This is consistent with recent evidence showing that 85% of buyers are not aware of potential foundation risks (Bani et al., 2024). Using Google Trends data, we further find that information on subsidence is not correctly priced when it is particularly salient, which supplements the salience argument in case of flood risk given by Giglio et al. (2021b). Moreover, the estimates indicate that buyers overestimate the risk of flooding. This is consistent with the findings of Bosker et al. (2019) that households expect a flood at least once every hundred years, which is significantly higher than the officially proclaimed state of the flood defenses.

An interesting avenue for future research would be to investigate how flood risk effects relate to the experience of actual flood events such as the flooding of Noord-Brabant and

Limburg in the Netherlands in 2021. Moreover, one of the main drivers of subsidence is local water management (Kok and Angelova, 2020). Therefore, losses in housing wealth should be considered by local authorities when setting optimal groundwater levels. Although this study does not explicitly include groundwater levels, it is unlikely to pose a threat to the empirical design as groundwater levels vary at a larger scale (Bootsma et al., 2020). Precisely this type of unobserved local variables is filtered out by the border discontinuity design. Further research should also quantify the effect on other sectors such as commercial real estate or infrastructure. Moreover, it would be useful to utilize structural hedonic models along the lines of Ekeland et al. (2004); Bajari and Benkard (2005); Bajari and Kahn (2005) that incorporate household characteristics to examine how the results vary across individuals. Finally, the mispricing of flood and subsidence risks found in this study supports the case for standardized disclosure of climate risks, for example, in the form of a climate label for real estate (Bani et al., 2024).

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A Robustness Checks

A.1 Inundation Depth

We investigate whether the effect of subsidence differs by inundation depth, the projected water levels a property is exposed to in the event of flooding. Appendix Figure B.5 shows the coefficient estimates for the interaction effect between future subsidence and five different categories of inundation depth. The estimates show that price effects of subsidence are concentrated among properties facing potential inundation depths between 20 cm and 80 cm. Those properties trade at a discount of approximately 3.5%. Properties that would be inundated by more than 80 cm do not trade at a discount. This is consistent with the hydrology literature, which typically models the relation between inundation depth and flood damage using a root function (Endendijk et al., 2023; Sieg and Thieken, 2022).

For properties with relatively low inundation depths, an increase in inundation depth caused by subsidence leads to a large increase in projected flood damages, while for properties that already face substantial projected inundation levels, the marginal increase in projected damage is much smaller. The corresponding estimates are shown in Column 1 of Appendix Table C.4. The other two columns repeat the same regression using different levels of flood risk (i.e., flooding every 1,000 and every 100 years, respectively). For the higher risk levels, the pattern is less clear, potentially due to the fact that fewer properties are affected by this degree of flood risk, which could make estimates more noisy. Furthermore, the baseline coefficient of future subsidence, which was insignificant in Column 1, becomes negative.

A.2 Distance to the Boundary

To identify the effect of subsidence on property prices, we apply a border discontinuity design. This approach compares affected properties along an imaginary boundary with properties on one side and unaffected properties on the other side. By comparing properties on both sides of the boundary, it is possible to reduce the bias arising from unobserved local amenities. Traditionally, studies applying this approach, such as Black (1999), define a distance cutoff and only include observations that fall within this distance to the border. Instead of arbitrarily defining a cutoff, we follow Gibbons et al. (2013) and weight each observation by the inverse distance to the boundary. To demonstrate that the results are not sensitive to this choice, Appendix Table C.2 shows estimates for a range of distance cutoffs.

Column 1 of Appendix Table C.2 shows the same estimates as Column 6 of Table 3, where observations are weighted with the inverse distance to the boundary. In Columns 2 to 6, we apply different distance cutoffs ranging from 50 to 1000 metres. Column 7 shows results of a naive OLS regression estimated on the full sample without sample restrictions or weights. The estimates of the interaction term between future subsidence and flood risk are relatively stable across all specifications. The effect size of current subsidence for properties built before 1980 substantially varies across specifications. For the most narrow threshold of 50 metres the coefficient is -0.0059 and it decreases to -0.0193 for the naive OLS estimation. While the interaction term with the construction period decreases in magnitude, the baseline effect of current subsidence is increasing across specifications. In the OLS specification in Column 7, the baseline effect of 0.0127 is significant at the 1% confidence level. The difference between the baseline effect and the interaction term is comparable to the effect from our preferred specification. The results suggest that current subsidence is correlated with unobserved amenities, i.e. current subsidence is more prevalent in desirable locations, where house prices are higher. This underlines the importance of applying BD to identify causal effects.

A.3 Alternative Fixed Effects

A common strategy to control for unobserved property level characteristics is to apply a repeat sales approach (Hino and Burke, 2021). Repeat sales identify effects from the sales of properties that sell more than once during the sample period, which allows for the inclusion of property fixed effects. In this application, however, we are unable to estimate a repeated sales regression, as there is no temporal variation in the explanatory variables of interest, current and future subsidence. Dröes and Koster (2021) show that the results of a repeat sales regression are very close to regressions that include very detailed location fixed effects. Therefore, we approximate a repeated sales regression by adding fixed effects at a more granular five- and six-digit zip code level. We further estimate a specification with 4PPC-by-year fixed effects to check for time-varying spatial trends.

The results of these robustness checks are reported in Appendix Table C.5. Column 1 reports the baseline results from Column 6 of Table 3 using 4PPC fixed effects. Column 2 shows the same estimates using 5PPC fixed effects. The magnitude of the coefficients decreases somewhat, but the significance levels remain unchanged. The specification in Column 3 estimates the model with 6PPC fixed effects instead. This further reduces the effect of subsidence on the price of buildings constructed before 1980 and reduces the significance level to 5%. The interaction effect between future subsidence and flood risk becomes positive and is no longer significant. A likely explanation of this finding is the spatial scale at which information is available. The median 6PPC covers an area of $60m \times 60m$, while the median 5PPC covers an area of $294m \times 294m$ (Bosker et al., 2019). In contrast, maps on future subsidence and flood risk have a resolution of $100m \times 100m$, which would imply very little variance in these variables *within* a 6PPC area. Thus, 6PPC fixed effects likely remove most of the identifying variation in these variables, even with the quality granular data we use in this study. Finding an insignificant *indirect* effect is, therefore, not surprising. For properties constructed before 1980, the effect of current subsidence, for which we have data at the property level, remains statistically significant. That this is the case, although properties in the same 6PPC area are exposed to the same environment, seems reassuring for the baseline estimates.

Column 4 reports estimates using 4PPC-by-year fixed effects. The coefficient on the *direct* effect slightly increases, while the interaction between future subsidence and flood risk remains virtually unchanged. This suggests that the effects obtained are not driven by local time trends.

A.4 Definition of Variables

For the baseline analysis, we define an indicator variable for current subsidence that equals one if the property experiences subsidence of 3.3 mm per year or more. Accordingly, for future subsidence the indicator captures whether the property is predicted to subside 10 cm or more between 2020 and 2050. These values are chosen because predicted subsidence of below 10 cm between 2020 and 2050 is classified as "limited subsidence" in the Climate Impact Atlas. A yearly subsidence rate of 3.3 mm corresponds to 10 cm over a time horizon of 30 years. Furthermore, construction experts state that subsidence has negative effects on a building beginning at a yearly rate of 3 mm (Willemsen et al., 2020). To assess the sensitivity of the results to this choice, Appendix Table C.7 shows results using alternative definitions of the subsidence variables.

In Column 1, we define the relevant cutoff as a yearly subsidence rate of 0 mm in which case the direct effect becomes positive and statistically insignificant. This might indicate that very low subsidence rates are associated with negligible effects. This is consistent with the estimation that negative effects of subsidence materialise once the yearly subsidence rate exceeds 3 mm (Willemsen et al., 2020). The interaction term between future subsidence and flood risk increases slightly. The relevant cutoff in Column 3 is a yearly subsidence rate of 6.7 mm. This corresponds to the classification of "extensive subsidence" in the prediction map. Current subsidence has a positive baseline effect of 0.021, which is significant at the 5% significance level. This indicates that locations with extensive rates of subsidence have positive unobserved amenities. The interaction between current subsidence and a property being built before 1980 is significant at the 1% significance level and relatively large at -0.335. After accounting for the positive baseline effect, the estimate suggests that properties built before 1980 that are exposed to more than 6.7 mm of subsidence per year trade at a discount of 1.2%. The interaction term between future subsidence and flood risk decreases slightly but becomes statistically insignificant. This is likely caused by the lower precision of the estimates, as subsidence rates of more than 6.7 mm per year are relatively rare, which implies that most of the identification comes from relatively few observations close to the boundary.

In our main specification we use a measure of uniform subsidence, which measures the weighted average of subsidence at the five closest measurement points surrounding a property. Kok and Angelova (2020) and Kok et al. (2021) suggest that not uniform but instead differential subsidence across the foundation of the property causes damages, specifically for buildings on shallow foundations. To test this hypothesis, we include differential subsidence measured by the maximum difference between the closest measurement points. The results are shown in Appendix Table C.6. First, we consider a property as exposed to differential subsidence if the maximum difference between measurement points is larger than 1 mm per year. This corresponds to the threshold determined by construction experts in Willemsen et al. (2020). We also test thresholds of 2 mm per year and 3.3 mm per year. The results show that the coefficients on the differential subsidence variables are not statistically significant. The remaining estimates are virtually unchanged compared to our baseline specification.

In addition, we test the sensitivity of the results to the choice of the level of flood risk. The results are shown in Appendix Table C.8. When considering the small (floods once in 1,000 years) and medium (floods once in 100 years) probabilities of flood risk, the effect of current subsidence on properties constructed before 1980 remains unchanged. The interaction effect between flood risk and future subsidence decreases and becomes statistically insignificant. However, the uninteracted effect of future subsidence increases and becomes statistically significant and comparable in size to the indirect effect from the baseline specification. This suggests that future subsidence has a significant negative price effect on properties that are exposed to flood risk but are expected to flood less than once per 1,000 years. A possible explanation could be that buyers consider flood risk a binary variable and do not distinguish between different degrees of flood risk.

In our preferred specification, property prices are regressed on both current and future subsidence and their respective interaction effects. In Appendix Table C.9 we show results only using current or future subsidence. The results for current subsidence are almost identical to the baseline estimates. When only future subsidence is included, the interaction effect between subsidence and flood risk increases, but the base effect of future subsidence becomes positive and statistically significant at the 10% significance level.

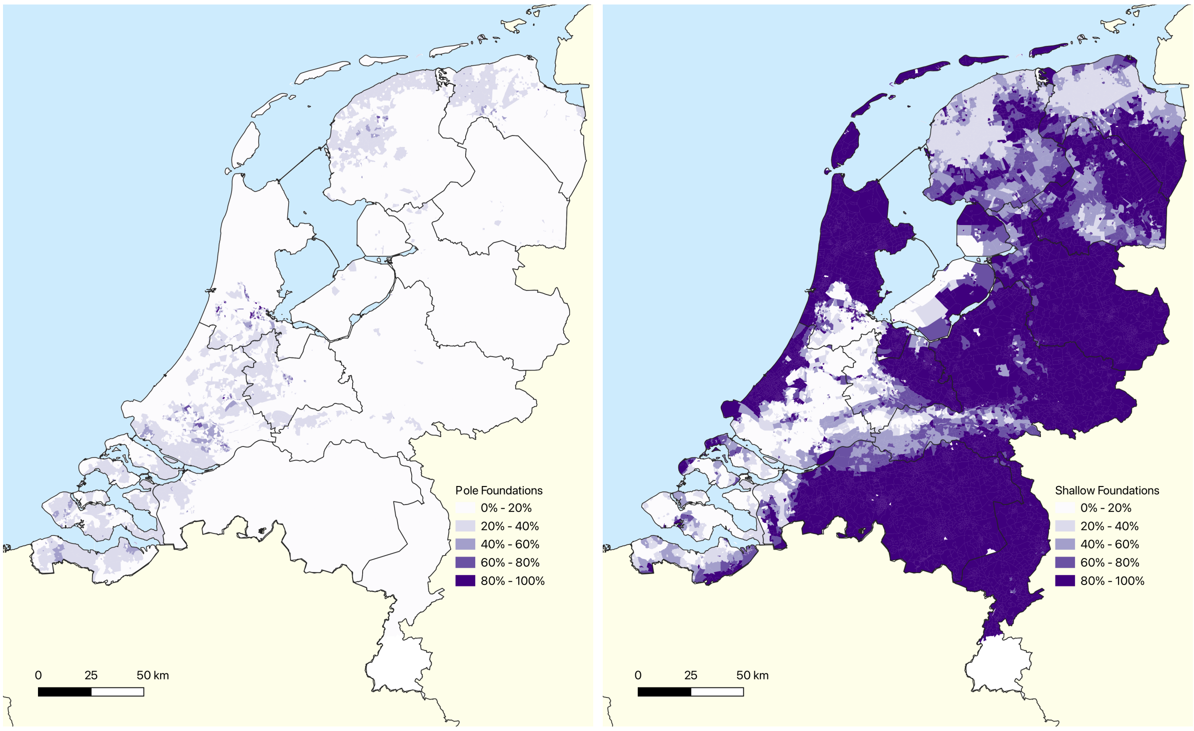
A.5 Other Sensitivity Analyses

To show that our results are not sensitive to our choice of variables and sample, we perform additional tests. The corresponding results are shown in Appendix Table C.10. In Column 2, we change the construction year cutoff from 1980 to 1970, see Section 4. The point estimate of the interaction between current subsidence and construction year increases somewhat in magnitude (from 0.008, see Column 1, to 0.0099). However, both coefficients are not statistically different from each other at a 5% significance level.

In addition, we impose a range of sample restrictions. First, we consider whether the estimates on flood risk are driven by the Western European Flood of 2021, which caused casualties and major damages across Eastern Belgium and Western Germany. Despite not causing any casualties in the Netherlands, the flood caused €350 - 600 million in damages, mainly in the province of Limburg (Kok et al., 2023). Thus, the flood might have had an impact on flood risk perceptions in the Netherlands. Second, the measure of current subsidence is based on measurements between 2017 and 2021. Therefore, it might not be an appropriate proxy for years predating the measurements. To test this, we restrict the sample to the years from 2017 to 2021, for which the trend of subsidence is a valid approximation by definition. Third, we exclude the province of Groningen as subsidence caused by the extraction of natural gas can cause earthquakes (Koster and van Ommeren, 2015), which might be more damaging than subsidence caused by dehydration of soft soils. In the fourth specification, we adopt a more granular definition of areas affected by earthquakes by following the CBS classification of affected neighbourhoods (CBS, 2020). Finally, we remove the province of Limburg, which seems to be an outlier as the ground appears to rise in certain locations. The results of these tests are presented in Appendix Table C.10. Most of the sample restrictions do not significantly affect the main results. The most notable exception is that in the specification for the years from 2017 to 2021, the interaction term between future subsidence and flood risk decreases somewhat and loses its statistical significance. However, the main concern of this test is to show that the trend in current subsidence between 2017 and 2021 is a valid approximation for the whole sample period. This seems to be the case as estimates of coefficients involving current subsidence remain almost unchanged.

B Additional Figures

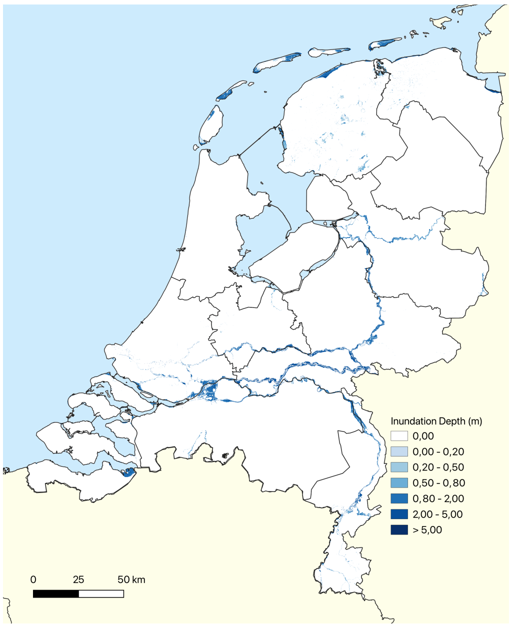
Figure B.1: Share of foundations at risk



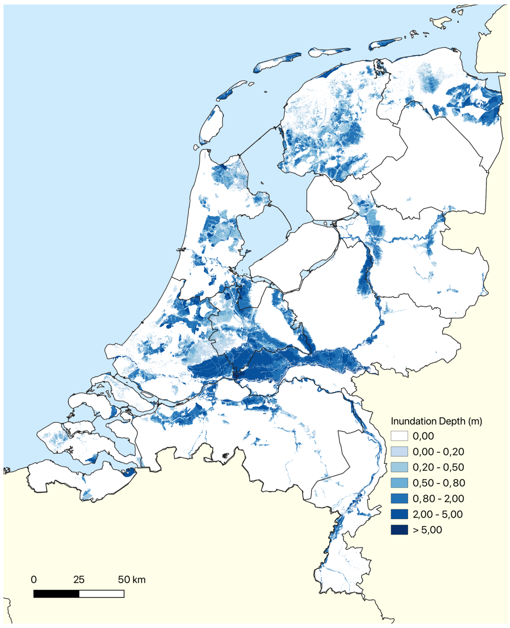
(a) Pole foundations (b) Shallow foundations

Note: The maps show the share of pole and shallow foundations among properties, which were constructed before the mid 1970s, at the neighbourhood level. The data is based on estimations from construction experts and obtained from the Climate Impact Atlas.

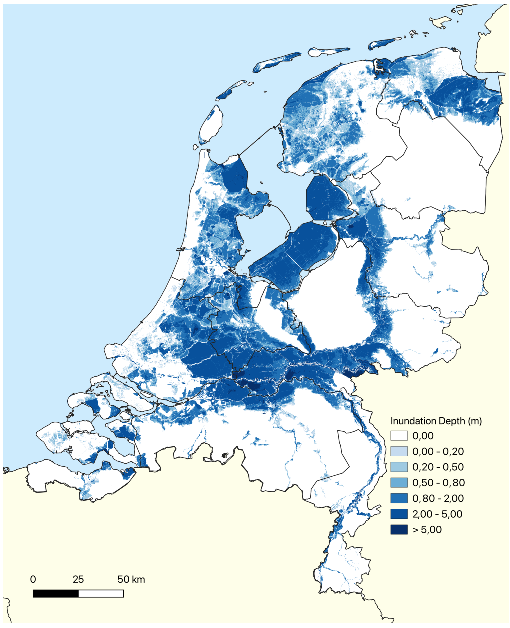
Figure B.2: Inundation depth, different risk levels



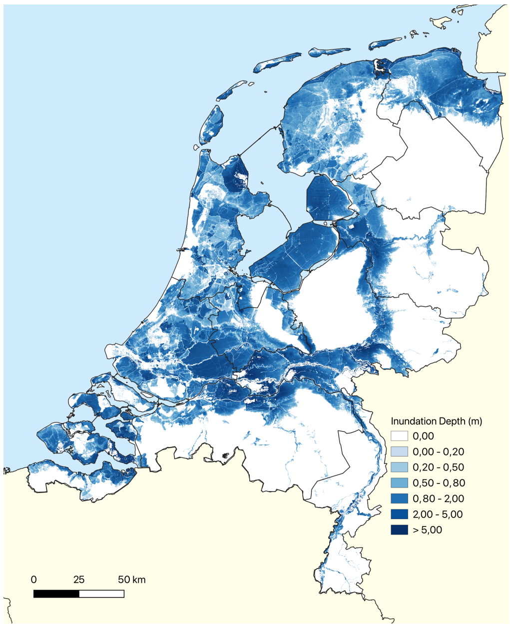
(a) Floods 1/10 years



(b) Floods 1/100 years



(c) Floods 1/1,000 years



(d) Floods 1/100,000 years

Note: The maps show the inundation depths in case of a failure of the primary flood defenses for four different levels of flood risk. According to the official safety standards, the flood defenses would fail once in 10 years, 100 years, 1,000 years, and 100,000 years respectively. The data is obtained from the Climate Impact Atlas.

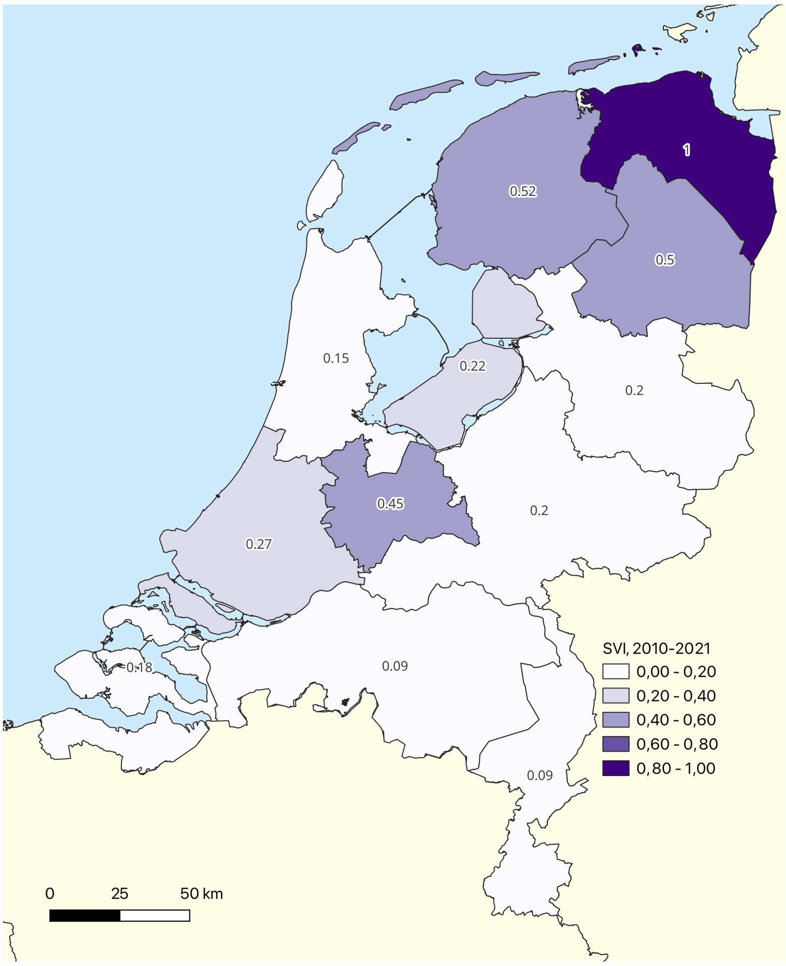
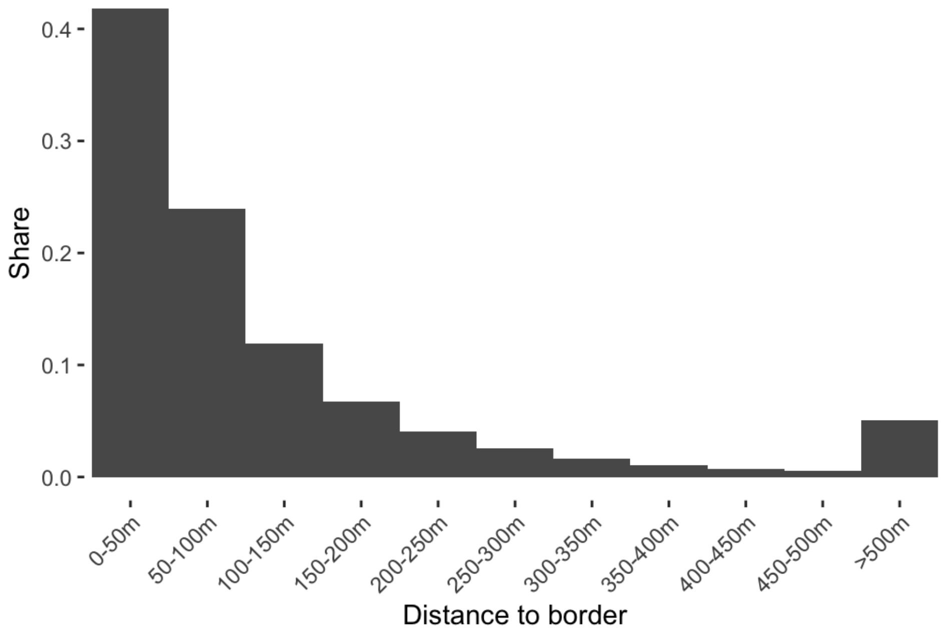


Figure B.3: Search volume intensity, spatial variation

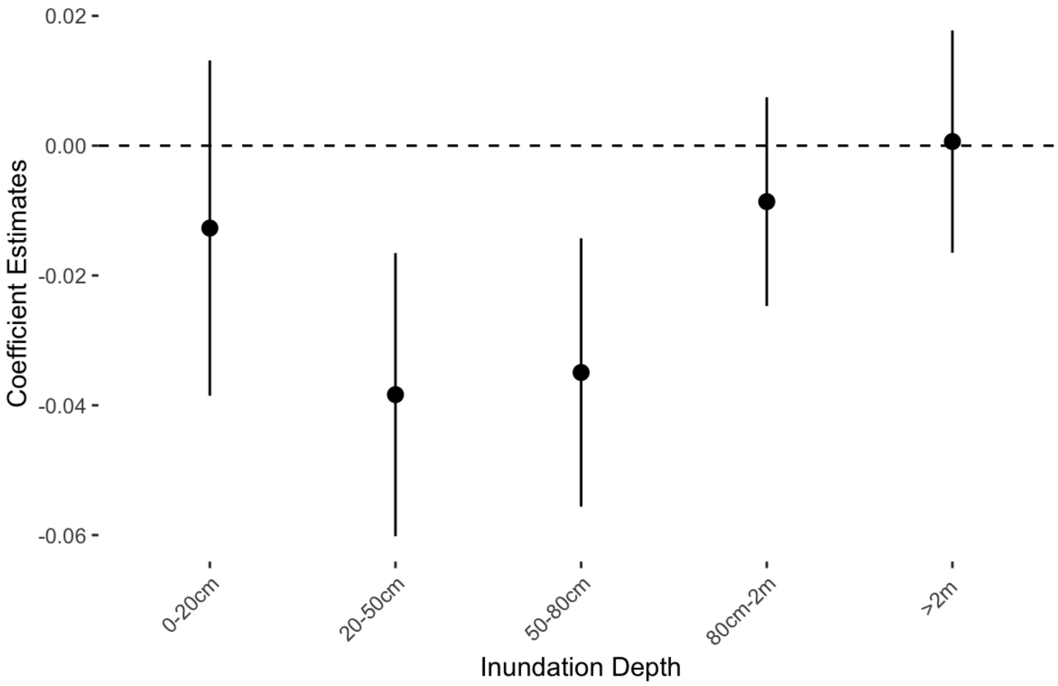
Note: The map shows spatial variation in google search frequency of the term land subsidence (in Dutch 'bodemdaling') at the province level. A value of 1 denotes the maximum search frequency.

Figure B.4: Distance to border



Note: The figure plots the share of properties with a certain distance to the boundary that falls within 50 meter bins. For properties that are subsiding by a significant amount of more than 3.3 mm per year the distance to the boundary is the distance to the nearest property that is subsiding by less than 3.3 mm per year. Conversely, for properties that are not exposed to significant subsidence we measure the distance to the nearest property that is affected by significant subsidence.

Figure B.5: Inundation depth and future subsidence



Note: The Figure shows the coefficient of the interaction term between the future subsidence dummy and different values of inundation depth. Standard errors are clustered at the 3PPC level. Coefficients correspond to the last five rows in Column 1 of Table C.4.

C Additional Tables

Table C.1: Correlation matrix

	Cur. subs.	Fut. subs.	Before 1980	Inundation	Pole rot vuln.	Differential settlement vuln.
Cur. subs.		0.122	0.015	0.135	0.165	0.182
Fut. subs.			-0.085	0.177	0.088	0.384
Before 1980				-0.064	0.084	-0.044
Inundation					0.136	0.266
Pole rot vuln.						0.211
Differential settlement vuln.						

Note: The table shows the correlation between current soil subsidence, future soil subsidence, a property being exposed to foundation risk, inundation depth under an extremely small probability of flooding (1/100,000 years), vulnerability to pole rot (affects properties on pole foundations) and vulnerability to differential settlement (affects properties on shallow foundations).

Table C.2: Different distance thresholds

	Log price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current subsidence > 3.3mm	0.0005	-0.0013	0.0042	0.0097***	0.0076**	0.0028	0.0127***
	(0.0024)	(0.0041)	(0.0033)	(0.0034)	(0.0035)	(0.0033)	(0.0034)
Future subsidence > 10cm	-0.0047	-0.0051	-0.0023	-0.0007	-0.0004	-0.0001	0.0009
	(0.0068)	(0.0061)	(0.0054)	(0.0050)	(0.0050)	(0.0051)	(0.0051)
Floods 1/100,000 years	-0.0077	-0.0083*	-0.0055	-0.0065	-0.0057	-0.0057	-0.0059
	(0.0062)	(0.0049)	(0.0043)	(0.0042)	(0.0040)	(0.0040)	(0.0039)
Current subsidence > 3.3mm × Built before 1980	-0.0080***	-0.0059**	-0.0097***	-0.0129***	-0.0156***	-0.0175***	-0.0193***
	(0.0022)	(0.0023)	(0.0027)	(0.0032)	(0.0034)	(0.0035)	(0.0036)
Future subsidence > 10cm × Built before 1980	0.0053	0.0022	0.0036	0.0025	0.0023	0.0021	0.0023
	(0.0074)	(0.0065)	(0.0062)	(0.0059)	(0.0058)	(0.0058)	(0.0059)
Current subsidence > 3.3mm × Floods 1/100,000 years	0.0019	-0.0012	-0.0025	-0.0037	-0.0030	-0.0028	-0.0045
	(0.0024)	(0.0021)	(0.0024)	(0.0027)	(0.0027)	(0.0027)	(0.0028)
Future subsidence > 10cm × Floods 1/100,000 years	-0.0152**	-0.0139**	-0.0155**	-0.0149**	-0.0144**	-0.0143**	-0.0156**
	(0.0074)	(0.0067)	(0.0064)	(0.0062)	(0.0062)	(0.0062)	(0.0063)
Observations	1,437,985	601,231	945,278	1,271,650	1,365,265	1,399,245	1,437,985
R^2	0.85437	0.85803	0.85297	0.84685	0.84431	0.84243	0.84157
Within R^2	0.69767	0.70611	0.70956	0.70951	0.70886	0.70715	0.70467
Year, Month and 4PPC fixed effects	✓	✓	✓	✓	✓	✓	✓
Property characteristics	✓	✓	✓	✓	✓	✓	✓
Distance polynomials	✓	✓	✓	✓	✓	✓	✓
Distance to border	IDW	< 50m	< 100m	< 250m	< 500m	< 1000m	full sample

Note: Standard errors are clustered at the 3PPC level. Column 1 shows our preferred specification from Column 6 of Table 3, which weights each observation by the inverse distance to the boundary. For subsiding properties this is defined as the distance to the nearest property that is not subsiding. For properties that are not subsiding, this is the distance to the nearest subsiding property. Instead of weighting each observation by the inverse distance, in Columns 2 to 6, we use a fixed distance band ranging from 50 metres to 1000 metres. In these regressions, we only include observations that fall within this specific distance band. Column 7 shows results of a fixed effects regression on the full sample without a border discontinuity strategy.
***p <0.01, **p <0.05, *p <0.1

Table C.3: Dependent variables

	Log price (1)	Log askprice (2)	Log time on market (3)
Current subsidence > 3.3mm	0.0005	0.0005	-0.0045
	(0.0024)	(0.0025)	(0.0114)
Future subsidence > 10cm	-0.0047	-0.0037	0.0083
	(0.0068)	(0.0071)	(0.0254)
Floods 1/100,000 years	-0.0077	-0.0110*	-0.0353**
	(0.0062)	(0.0063)	(0.0155)
Current subsidence > 3.3mm × Built before 1980	-0.0080***	-0.0065***	0.0164
	(0.0022)	(0.0023)	(0.0114)
Future subsidence > 10cm × Built before 1980	0.0053	0.0041	-0.0075
	(0.0074)	(0.0076)	(0.0274)
Current subsidence > 3.3mm × Floods 1/100,000 years	0.0019	0.0013	0.0031
	(0.0024)	(0.0024)	(0.0104)
Future subsidence > 10cm × Floods 1/100,000 years	-0.0152**	-0.0164**	-0.0175
	(0.0074)	(0.0077)	(0.0226)
Observations	1,437,985	1,437,985	1,437,985
R^2	0.85437	0.84395	0.23434
Within R^2	0.69767	0.70608	0.04619
Year, Month and 4PPC fixed effects	✓	✓	✓
Property characteristics	✓	✓	✓
Distance polynomials	✓	✓	✓

Note: Standard errors are clustered at the 3PPC level. Observations are weighted by the inverse distance to the boundary. Column 1 shows our baseline results using log transaction price as dependent variable. Column 2 estimates the equation using the log askprice as dependent variable. In Column 3, we change the dependent variable to (log) time on market. ***p <0.01, **p <0.05, *p <0.1

Table C.4: Inundation depth

	Log price		
	(1)	(2)	(3)
Current subsidence > 3.3mm	0.0005	0.0014	0.0019
	(0.0024)	(0.0022)	(0.0019)
Future subsidence > 10cm	-0.0069	-0.0134**	-0.0161***
	(0.0066)	(0.0064)	(0.0050)
Inundation 0-20cm	-0.0037	-0.0071	0.0099
	(0.0057)	(0.0085)	(0.0090)
Inundation 20-50cm	-0.0032	-0.0008	0.0021
	(0.0057)	(0.0080)	(0.0073)
Inundation 50-80cm	-0.0016	0.0022	0.0093
	(0.0074)	(0.0080)	(0.0097)
Inundation 80cm-2m	-0.0129	-0.0052	0.0155
	(0.0081)	(0.0081)	(0.0104)
Inundation > 2m	-0.0281**	-0.0151	0.0126
	(0.0131)	(0.0108)	(0.0137)
Current subsidence > 3.3mm × Built before 1980	-0.0082***	-0.0079***	-0.0082***
	(0.0021)	(0.0022)	(0.0022)
Future subsidence > 10cm × Built before 1980	0.0070	0.0049	0.0063
	(0.0066)	(0.0072)	(0.0074)
Current subsidence > 3.3mm × Inundation 0-20cm	0.0038	-0.0021	-0.0002
	(0.0042)	(0.0047)	(0.0039)
Current subsidence > 3.3mm × Inundation 20-50cm	0.0089*	0.0049	0.0024
	(0.0050)	(0.0046)	(0.0041)
Current subsidence > 3.3mm × Inundation 50-80cm	0.0025	0.0019	0.0051
	(0.0033)	(0.0031)	(0.0041)
Current subsidence > 3.3mm × Inundation 80cm-2m	-0.0009	0.0005	-0.0056
	(0.0027)	(0.0027)	(0.0045)
Current subsidence > 3.3mm × Inundation > 2m	0.0017	-0.0001	-0.0017
	(0.0027)	(0.0032)	(0.0037)
Future subsidence > 10cm × Inundation 0-20cm	-0.0127	0.0103	-0.0004
	(0.0132)	(0.0110)	(0.0090)
Future subsidence > 10cm × Inundation 20-50cm	-0.0384***	-0.0134	-0.0013
	(0.0111)	(0.0092)	(0.0088)
Future subsidence > 10cm × Inundation 50-80cm	-0.0350***	-0.0246**	-0.0058
	(0.0105)	(0.0112)	(0.0114)
Future subsidence > 10cm × Inundation 80cm-2m	-0.0086	-0.0129	-0.0083
	(0.0082)	(0.0108)	(0.0151)
Future subsidence > 10cm × Inundation > 2m	0.0006	0.0166*	0.0145
	(0.0087)	(0.0100)	(0.0158)
Observations	1,437,985	1,437,985	1,437,985
R^2	0.85447	0.85438	0.85435
Within R^2	0.69789	0.69770	0.69764
Year, Month and 4PPC fixed effects	✓	✓	✓
Property characteristics	✓	✓	✓
Distance polynomials	✓	✓	✓
Flood risk	1/100,000 years	1/1,000 years	1/100 years

Note: Standard errors are clustered at the 3PPC level. Observations are weighted by the inverse distance to the boundary. The regressions in the table replace the indicator variable for flood risk with five categories of inundation depth. The regression is conducted for three different levels of flood risk 1/100,000 years, 1/1,000 years, and 1/100 years respectively. ***p <0.01, **p <0.05, *p <0.1

Table C.5: Robustness checks

	Log price			
	(1)	(2)	(3)	(4)
Current subsidence > 3.3mm	0.0005	-0.0005	0.0006	0.0019
	(0.0024)	(0.0017)	(0.0017)	(0.0023)
Future subsidence > 10cm	-0.0047	0.0033	-0.0041	-0.0052
	(0.0068)	(0.0052)	(0.0053)	(0.0066)
Floods 1/100,000 years	-0.0077	0.0015	0.0013	-0.0061
	(0.0062)	(0.0037)	(0.0027)	(0.0061)
Current subsidence > 3.3mm × Built before 1980	-0.0080***	-0.0053***	-0.0033**	-0.0093***
	(0.0022)	(0.0016)	(0.0015)	(0.0021)
Future subsidence > 10cm × Built before 1980	0.0053	-0.0015	0.0021	0.0055
	(0.0074)	(0.0051)	(0.0057)	(0.0074)
Current subsidence > 3.3mm × Floods 1/100,000 years	0.0019	0.0029*	0.0022	0.0006
	(0.0024)	(0.0018)	(0.0016)	(0.0022)
Future subsidence > 10cm × Floods 1/100,000 years	-0.0152**	-0.0106**	0.0046	-0.0151**
	(0.0074)	(0.0053)	(0.0051)	(0.0071)
Observations	1,437,985	1,437,985	1,437,985	1,437,985
R^2	0.85437	0.88980	0.93334	0.87528
Within R^2	0.69767	0.63494	0.48512	0.71910
Year and Month fixed effects	✓	✓	✓	
4PPC fixed effects	✓			
5PPC fixed effects		✓		
6PPC fixed effects			✓	
Year-4PPC fixed effects				✓
Property characteristics	✓	✓	✓	✓
Distance polynomials	✓	✓	✓	✓
Fixed Effects	4PPC	5PPC	6PPC	4PPC by year

Note: Standard errors are clustered at the 3PPC level. Observations are weighted by the inverse distance to the boundary. Column 1 shows the results from our preferred specification from Column 6 of Table 3 using four-digit zip-code fixed effects. Columns 2 and 3 replace the fixed effects with five-digit and six-digit zip-code fixed effects respectively. Column 4 applies four-digit × year fixed effects. ***p <0.01, **p <0.05, *p <0.1

Table C.6: Differential subsidence

	Log price		
	(1)	(2)	(3)
Current subsidence > 3.3mm	0.0006	0.0013	0.0004
	(0.0024)	(0.0024)	(0.0024)
Differential subsidence	-0.0017	-0.0091	-0.0005
	(0.0035)	(0.0056)	(0.0102)
Future subsidence > 10cm	-0.0047	-0.0043	-0.0048
	(0.0069)	(0.0069)	(0.0068)
Floods 1/100,000 years	-0.0064	-0.0085	-0.0078
	(0.0067)	(0.0063)	(0.0063)
Current subsidence > 3.3mm × Built before 1980	-0.0081***	-0.0083***	-0.0076***
	(0.0022)	(0.0023)	(0.0022)
Differential subsidence × Built before 1980	0.0004	0.0020	-0.0080
	(0.0034)	(0.0044)	(0.0076)
Future subsidence > 10cm × Built before 1980	0.0053	0.0052	0.0057
	(0.0075)	(0.0075)	(0.0074)
Current subsidence > 3.3mm × Floods 1/100,000 years	0.0021	0.0016	0.0019
	(0.0024)	(0.0024)	(0.0024)
Differential subsidence × Floods 1/100,000 years	-0.0021	0.0042	0.0017
	(0.0028)	(0.0051)	(0.0095)
Future subsidence > 10cm × Floods 1/100,000 years	-0.0152**	-0.0154**	-0.0152**
	(0.0074)	(0.0074)	(0.0074)
Observations	1,437,985	1,437,985	1,437,985
R^2	0.85437	0.85438	0.85437
Within R^2	0.69768	0.69770	0.69768
Year, Month and 4PPC fixed effects	✓	✓	✓
Property characteristics	✓	✓	✓
Distance polynomials	✓	✓	✓
Differential subsidence	> 1 mm/year	> 2 mm/year	> 3.3 mm/year

Note: Standard errors are clustered at the 3PPC level. Observations are weighted by the inverse distance to the boundary. In the Table, we include differential subsidence. The indicator variable takes the value one if the maximum difference in yearly subsidence rates of a property's five closest measurement points is above a certain threshold. In Column 1, this threshold is a difference of 1 mm/year. Columns 2 and 3 change the threshold to 2 mm/year and 3.3 mm/year respectively.
***p <0.01, **p <0.05, *p <0.1

Table C.7: Current subsidence variables

	Log price			
	(1)	(2)	(3)	(4)
Current subsidence	2.196	0.0018	0.0005	0.0210**
	(1.994)	(0.0025)	(0.0024)	(0.0092)
Future subsidence	-0.0020	0.0053	-0.0047	-0.0037
	(0.0219)	(0.0101)	(0.0068)	(0.0151)
Floods 1/100,000 years	-0.0064	0.0039	-0.0077	-0.0157
	(0.0065)	(0.0064)	(0.0062)	(0.0102)
Current subsidence × Built before 1980	-7.724***	0.0034	-0.0080***	-0.0335***
	(2.091)	(0.0023)	(0.0022)	(0.0097)
Future subsidence × Built before 1980	0.0092	-0.0047	0.0053	0.0218*
	(0.0220)	(0.0087)	(0.0074)	(0.0121)
Current subsidence × Floods 1/100,000 years	0.8607	-0.0037*	0.0019	-0.0060
	(1.957)	(0.0021)	(0.0024)	(0.0078)
Future subsidence × Floods 1/100,000 years	-0.0615***	-0.0198**	-0.0152**	-0.0212
	(0.0214)	(0.0087)	(0.0074)	(0.0155)
Observations	1,437,985	1,437,985	1,437,985	1,437,985
R^2	0.85438	0.84946	0.85437	0.86310
Within R^2	0.69769	0.70062	0.69767	0.69694
Year, Month and 4PPC fixed effects	✓	✓	✓	✓
Property characteristics	✓	✓	✓	✓
Distance polynomials	✓	✓	✓	✓
Subsidence variable	Continuous	> 0mm	> 3.3mm	> 6.7mm
Boundary	> 3.3mm	> 0mm	> 3.3mm	> 6.7mm

Note: Standard errors are clustered at 3PPC level. In Column 1 we treat land subsidence in metres as a continuous variable. In Column 2 we define a property as exposed if it is subsiding at a positive rate. Column 2 shows our baseline estimates from Column 6 of Table 3 where a property is affected if it subsides by more than 3.3 mm per year. Column 4 uses a yearly subsidence rate of 6.7 mm as cutoff. Observations are weighted by the inverse distance to the boundary between properties exposed to current subsidence and unaffected properties, which are defined according to the cutoff used in the regression. ***p <0.01, **p <0.05, *p <0.1

Table C.8: Different levels of flood risk

	Log price		
	(1)	(2)	(3)
Current subsidence > 3.3mm	0.0005	0.0014	0.0018
	(0.0024)	(0.0022)	(0.0019)
Future subsidence > 10cm	-0.0047	-0.0136**	-0.0161***
	(0.0068)	(0.0064)	(0.0050)
Flood risk	-0.0077	-0.0044	0.0089
	(0.0062)	(0.0068)	(0.0070)
Current subsidence > 3.3mm × Built before 1980	-0.0080***	-0.0080***	-0.0081***
	(0.0022)	(0.0022)	(0.0022)
Future subsidence > 10cm × Built before 1980	0.0053	0.0053	0.0064
	(0.0074)	(0.0072)	(0.0074)
Current subsidence > 3.3mm × Flood risk	0.0019	0.0007	-0.0004
	(0.0024)	(0.0022)	(0.0022)
Future subsidence > 10cm × Flood risk	-0.0152**	-0.0039	-0.0015
	(0.0074)	(0.0082)	(0.0070)
Observations	1,437,985	1,437,985	1,437,985
R^2	0.85437	0.85434	0.85434
Within R^2	0.69767	0.69761	0.69762
Year, Month and 4PPC fixed effects	✓	✓	✓
Property characteristics	✓	✓	✓
Distance polynomials	✓	✓	✓
Flood Risk	1/100,000 years	1/1,000 years	1/100 years

Note: Standard errors are clustered at the 3PPC level. Observations are weighted by the inverse distance to the boundary between properties exposed to current subsidence and unaffected properties. Column 1 shows the estimates from our preferred specification from Column 6 of Table 3. Columns 2 and 3 repeat the regression for properties that are exposed to a higher degree of flood risk and expected to flood once every 1,000 or once every 100 years. ***p <0.01, **p <0.05, *p <0.1

Table C.9: Current and future subsidence

	Log price		
	(1)	(2)	(3)
Current subsidence > 3.3mm	0.0005	0.0004	
	(0.0024)	(0.0024)	
Future subsidence > 10cm	-0.0047		0.0084*
	(0.0068)		(0.0044)
Floods 1/100,000 years	-0.0077	-0.0097	-0.0057
	(0.0062)	(0.0059)	(0.0060)
Current subsidence > 3.3mm × Built before 1980	-0.0080***	-0.0077***	
	(0.0022)	(0.0022)	
Future subsidence > 10cm × Built before 1980	0.0053		0.0024
	(0.0074)		(0.0041)
Current subsidence > 3.3mm × Floods 1/100,000 years	0.0019	0.0017	
	(0.0024)	(0.0024)	
Future subsidence > 10cm × Floods 1/100,000 years	-0.0152**		-0.0189***
	(0.0074)		(0.0049)
Observations	1,437,985	1,438,093	1,437,985
R^2	0.85437	0.85430	0.86135
Within R^2	0.69767	0.69762	0.70632
Year, Month and 4PPC fixed effects	✓	✓	✓
Property characteristics	✓	✓	✓
Distance polynomials	✓	✓	✓

Note: Standard errors are clustered at the 3PPC level. Observations are weighted by the inverse distance to the boundary. Column 1 shows results from our preferred specification shown in Column 6 of Table 3. In Columns 2 and 3 we investigate the effects of current and future subsidence separately. ***p <0.01, **p <0.05, *p <0.1

Table C.10: Other sensitivity analyses

	Log price						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current subsidence > 3.3mm	0.0005	0.0002	0.0004	0.0019	-0.0010	-0.0005	0.0004
	(0.0024)	(0.0022)	(0.0024)	(0.0029)	(0.0025)	(0.0024)	(0.0025)
Future subsidence > 10cm	-0.0047	0.0026	-0.0046	-0.0044	-0.0057	-0.0045	-0.0049
	(0.0068)	(0.0063)	(0.0068)	(0.0072)	(0.0068)	(0.0069)	(0.0069)
Floods 1/100,000 years	-0.0077	-0.0077	-0.0080	-0.0074	-0.0083	-0.0081	-0.0088
	(0.0062)	(0.0062)	(0.0062)	(0.0070)	(0.0062)	(0.0062)	(0.0062)
Current subsidence > 3.3mm × Built before cutoff	-0.0080***	-0.0099***	-0.0079***	-0.0086***	-0.0072***	-0.0074***	-0.0078***
	(0.0022)	(0.0023)	(0.0022)	(0.0023)	(0.0022)	(0.0022)	(0.0022)
Future subsidence > 10cm × Built before cutoff	0.0053	-0.0103	0.0055	0.0042	0.0063	0.0049	0.0049
	(0.0074)	(0.0086)	(0.0076)	(0.0074)	(0.0075)	(0.0074)	(0.0074)
Current subsidence > 3.3mm × Floods 1/100,000 years	0.0019	0.0018	0.0016	0.0013	0.0016	0.0018	0.0017
	(0.0024)	(0.0025)	(0.0024)	(0.0026)	(0.0025)	(0.0024)	(0.0025)
Future subsidence > 10cm × Floods 1/100,000 years	-0.0152**	-0.0160**	-0.0159**	-0.0128*	-0.0145*	-0.0150**	-0.0145**
	(0.0074)	(0.0073)	(0.0075)	(0.0072)	(0.0074)	(0.0074)	(0.0074)
Observations	1,437,985	1,437,985	1,393,017	691,753	1,386,834	1,417,803	1,380,596
R^2	0.85437	0.85438	0.85101	0.86521	0.85461	0.85462	0.85619
Within R^2	0.69767	0.69770	0.69891	0.71695	0.69874	0.69832	0.70000
Year, Month and 4PPC fixed effects	✓	✓	✓	✓	✓	✓	✓
Property characteristics	✓	✓	✓	✓	✓	✓	✓
Distance polynomials	✓	✓	✓	✓	✓	✓	✓
Construction year cutoff	1980	1970	1980	1980	1980	1980	1980
Sample Restriction	-	-	Pre-Flood	2017-2021	Groningen	Earthquakes	Limburg

Note: Standard errors are clustered at the 3PPC level. Observations are weighted by the inverse distance to the boundary. Column 1 presents baseline estimates. Column 2 changes the construction year cutoff to 1970. Column 3 restricts the sample to properties that were sold before the Wester European Flood of 2021, i.e. properties sold before July 2021. Column 4 uses the shorter sample period 2017-2021. Column 5 excludes all transactions in the province of Groningen. Column 6 excludes neighbourhoods affected by earthquakes realted to gas extraction in the northeastern part of the Netherlands based on the CBS classification. Column 7 excludes all transactions in the province of Limburg. ***p <0.01, **p <0.05, *p <0.1