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Dutch dilemma: Housing prices and flood risk exposure

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Abstract

This article studies the impact of flood risk exposure on housing prices in a major river delta. Analyzing 1.8 million property transactions from 1998 to 2023 in the Netherlands, we find an average price discount of 1.1%. We observe considerable heterogeneity in price effects driven by exposure intensity, institutional settings that vary across flood zones, time, and buyer sophistication. Our results suggest that homeowners incorporate flood risk in their buying decisions. However, collective adaptation measures considerably mitigate these negative price effects. The costs of adaptation projects seem relatively small in comparison to the economic value they create through shielding the housing market from flood risk.

KEYWORDS
Flood risk capitalization, Housing market, Physical climate risk, Institutional adaptation

1 | INTRODUCTION

Climate change increases both the frequency and intensity of extreme environmental events (Coumou & Rahmstorf, 2012) with flooding as a prime and tangible example. An asset class particularly vulnerable to increased flood risk is real estate. Because of their fixed nature, properties cannot easily adapt to flood risk. This would require considerable investments in the asset, the surroundings, or both. In addition, real estate values are largely determined by location, and therefore, flood risk can affect real estate assets by deteriorating location quality.

The threat that flooding imposes on real estate is concerning given the importance of this asset class for financial institutions. Large property devaluations can cause economic instability, exposing institutional investors and mortgage providers to considerable losses (Huang et al., 2022; Holtermans et al., 2024; Krueger et al., 2020; Ouazad & Kahn, 2022; Zhang et al., 2018). The effect of flooding on real estate markets is particularly large as much of the "prime" real estate is located close to water, either along coastlines or rivers, for example, New York, London, Shanghai, Rotterdam, etc.

For households, real estate-related climate risk might play an even more significant role. Owner-occupied homes are the main source of household wealth in most OECD countries and represent roughly 50% of the average household asset portfolio (OECD, 2022). Real estate serves as an important consumption channel, as price variations strongly affect consumer spending (Case et al., 2005). Hence, fluctuations in home prices considerably affect household wealth. The question is whether markets are sufficiently aware of climate risks, such as flood risk. Failing to account for these risks can lead to overpricing and price shocks once markets start to price them in (Gourevitch et al., 2023).

This article adds to a rapidly developing body of literature focusing on the pricing of physical climate risk. To deepen the understanding of asset market responses toward physical climate risk, we examine the impact of flood risk on housing prices in the Netherlands. This provides an interesting test case for two reasons. First, the Netherlands is a major river delta. River deltas are home to approximately 4.5% of the global population and are disproportionately affected by climate change (Edmonds et al., 2020). Because of their low elevation, river deltas are especially prone to flood risk (Caloia & Jansen, 2021). Unlike other coastal areas, where one type of flood risk tends to dominate, river deltas face a joint risk from storm surges, flash floods, and river floods (Budiyono et al., 2015; Chan et al., 2021; Mai et al., 2009). These threats are not isolated but compound each other—for example, high sea water levels reduce the discharge capacity of river systems and therefore add to river flood risk—and can lead to combined events that are both extreme and difficult to forecast (Qiu et al., 2022; Zscheischler et al., 2018). In addition to being subject to significant and unique flood threats, deltas tend to be densely populated (Nicholls et al., 2020). This not only enhances exposure but also intensifies competition for land and limits the availability of risk-free alternatives. Second, the Netherlands is highly exposed to flood risk, but also has a long, 70-year history of adaptation to threats posed by water. By examining price effects of flood risk exposure in this context, we can draw lessons about the implications of adaptation. Moreover, to mitigate flood risk, the country developed a unique collective approach with specific institutions in charge of water management. Examining the pros and cons of this collective approach can yield important policy lessons for water management in other areas.

We exploit variation in flood exposure—both across space and over time—to assess the impact of flood risk on housing prices, using a sample of 1.8 million transactions between 1998 and 2023. The Netherlands has various levels of flood risk exposure and protection systems. To examine the price effects of the joint flood risk exposure from storm surges, dike failure, and river overflow, we examine unembanked, primary-dike, secondary-dike, and local river areas that are prone to one or multiple of these flood threats. Our study results show consistent evidence that flood risk is priced in the housing market, but with considerable heterogeneity. The differences in discounts are not only driven by actual flood risk exposure, but also by financial exposure, such as insurance and disaster compensation policies. In line with the literature, we observe that sophisticated buyers demand larger price discounts as compared to less sophisticated buyers, indicating that risk salience might be a significant driver of discount heterogeneity. We also observe an overall time trend in which discounts become stronger. The observed change in the effect is small but significant, suggesting that home buyers have become more aware of flood risk exposure, or have started to incorporate increased exposure expectations due to climate change.

The findings in this article have implications for policy-makers tasked with responding to flood risk specifically, and climate risks more broadly. The results suggest that, while housing markets actively price flood risk exposure, adaptation strategies can limit the loss of economic value (for now). Collective water protection schemes, combined with transparent compensation programs, can strengthen market confidence in the protection of exposed areas. The costs of such adaptation appear to be relatively small in comparison to the value of the capital stock exposed to flooding—although this is situation-dependent. Collective adaptation thus keeps exposed areas attractive, which can be especially useful in densely populated river deltas where space is scarce. At the same time, collective adaptation yields the risk of increasing exposure rather than reducing it, as individuals have little incentive to avoid risk-prone areas. Section 2 provides an overview of the literature, but we highlight three related studies here: the works of Bosker et al. (2019); Mutlu et al. (2023); Daniel et al. (2009) focus on flood risk pricing in a similar setting. Our study differs in four important aspects. First, we compare discounts across flood risk zones with distinct compensation and insurance policies—allowing us to explore pricing heterogeneity driven by financial exposure. Second, we measure exposure through annual expected damage rather than examining maximum inundation and flood probability separately. This integrated measure enables risk assessment of many individual, but highly correlated flood scenarios and aligns more closely with insurance industry standards on flood risk assessment. Third, our identification strategy distinguishes treatment and control at the property level.[1] Using individual-level house price data not only provides more detailed estimates and a narrower definition of treatment and control groups, but it also enables us to account for property-specific elevation structures that are not consistently captured in flood zone maps. Last, none of the studies distinguishes between already existing risks versus new risks stemming from climate change. By examining the development of flood-risk-related discounts over a period of more than two decades, we provide insights into the effects of ever-present exposure and the marginal effects induced by climate change.

The remainder of this study is structured as follows: In Section 2, we provide an overview of the related literature. In Section 3, we introduce the institutional setting in which our empirical analysis takes place. In Section 4, we describe our empirical approach more formally. Section 5 discusses the data we use. Section 6 presents our results. In Section 7, we discuss policy and industry implications by generalizing our findings, and conclude.

2 | RELATED LITERATURE

Prior studies show that flood risk is capitalized in real estate prices, but with considerable heterogeneity (Beltrán et al., 2018; Contat et al., 2024; Schuetz, 2024). Drivers of this heterogeneity involve variation in physical exposure (Bernstein et al., 2019; Bosker et al., 2019; Murfin & Spiegel, 2020), financial exposure (Gete et al., 2024; Kousky et al., 2020; Keys & Mulder, 2020; Oh et al., 2022; Ouazad & Kahn, 2022), risk salience (Bakkensen & Barrage, 2022; Ellen & Meltzer, 2024; Fairweather et al., 2024; Hino & Burke, 2021; Niu et al., 2025), and climate beliefs (Baldauf et al., 2020; Bernstein et al., 2019; Gibson & Mullins, 2020).

[1] This particularly distinguishes the paper from Bosker et al. (2019) who rely on annual median six-digit postal codes.

In addition to studies documenting the impact of slow-moving, (chronic) climate risk, there is a substantial literature focusing on the impact of climate shocks, such as hurricanes and flood events (Addoum et al., 2023; Ellen and Meltzer, 2024; Garbarino & Guin, 2021; Niu et al., 2025; Ortega & Taspınar, 2018). A frequently occurring pattern in this literature is a decrease in asset values directly after an event, which then slowly recedes in the subsequent years. This effect suggests that markets require frequent information updates that signal risk or that risk tends to be overestimated directly after a climate shock.

As a natural follow-up to risk pricing studies, recent studies have examined the price effects of flood adaptation. Findings of such studies are mixed. Hovekamp and Wagner (2023) analyze the costs of private adaptation measures for individual properties. The authors find that elevating buildings in flood-prone areas reduces flood insurance claims, and argue that this form of adaptation is worth the investment for newly built homes in risky areas. For existing buildings, the costs of retrofitting are higher and exceed the risk mitigation benefits. Interestingly, the authors argue—based on the work of Ostriker and Russo (2024)—that expected elevation benefits are not capitalized in resale values, causing underinvestment in adaptation. Related studies examine the impact of public adaptation programs on private property prices. Mutlu et al. (2023) find strong positive price effects of adaptation programs. However, these effects are mainly driven by positive adjustments to the surroundings, rather than reduced risk levels. A paper by Bradt and Aldy (2025) provides convincing evidence that flood risk mitigation—caused by collective adaptation programs—affects property prices. The authors estimate that newly built levees increase the value of protected houses by 3%–4%. Notably, levees increase flood risk in their unprotected surroundings. These spillovers reduce home values in nearby areas by 1%–5%, largely offsetting adaptation benefits.

A related branch of literature examines climate gentrification patterns in risk-sensitive areas or post climate events. These studies address inequality concerns that can be driven by climate risk exposure. Galster et al. (2024) find that flood exposure varies significantly across ethnic groups, even when controlling for neighborhood income compositions. Vice versa, when controlling for neighborhood ethnic composition, they find that lower-income groups exhibit higher flood exposure in inland areas. Ellen and Meltzer (2024) documents that post-hurricane discounts are most persistent in low-income areas, and that climate events can change demographic trends, with lower-income non-white buyers sorting into these areas. A similar pattern is observed by Bradt & Aldy (2025), who find evidence of racial sorting after levee constructions. Interestingly, Varela Varela (2023) suggests that flood exposure does not necessarily lead to neighborhood depreciation. The author finds that exposed high-income neighborhoods attracted more high-income buyers and sold for higher prices after the Hurricane Sandy event than comparable neighborhoods without exposure. The posed rationale for this effect is that credit-constrained households derive higher disutility from flood events and thus sort into other places.

Finally, several studies apply (spatial) equilibrium models to analyze optimal adaptation (Fried, 2022; Ouazad & Kahn, 2025), construction decisions (Bunten & Kahn, 2017), mortgage markets (Gete et al., 2024; Ouazad & Kahn, 2022), and household wealth outcomes (Van der Straten, 2023).

While the literature provides convincing evidence of flood risk pricing and explains many of the factors that drive heterogeneity, important channels that could drive variation in exposure pricing remain unexplored. Moreover, present studies tend to focus on sea-level rise and water damage caused by hurricanes, with particular emphasis on the United States. Far less attention is paid to inland flood risk caused by river overflow or dike breaches, which are relevant both in the United States and in other geographies. In addition, the literature highlights the challenges of assessing whether observed discounts are rational or not. Observed price effects can be biased by water amenities that are correlated with flood risk. While studies account for these amenities, doing so in a systematic way proves difficult (Atreya & Czajkowski, 2019).

Even when observed risk pricing is completely unbiased, uncertainty surrounding climate change remains. While we know that climate change adds risk, exact impacts—specifically at the local level—remain unclear, due to the inadequacy of climate risk models. Beyond modeling uncertainty, future emission pathways remain unknown, and neither do we know to what extent society can adapt to an altering climate (Millner et al., 2013).

3 | INSTITUTIONAL SETTING

3.1 | Flood risk in the Netherlands

The Dutch coastal delta is a densely populated country prone to multiple flood threats. The country borders the North Sea in the North and West. Many places in these parts of the country are located below sea level. Because of this low elevation, many properties and households in the North and West face a direct threat of coastal flooding. Inland, two major river systems induce flood risk to their surroundings. One of them (the Meuse) is fed by rainwater and flows from the South to the West. The other river (the Rhine) is fed by rain and melt-water and runs from East to West. In addition, the country has several regional river systems. These systems drain local precipitation in normal circumstances but can overflow in case of heavy rainfall. Consequently, even without considering the effects of climate change, around 34% of the country's surface area and 35% of the population—approximately 6.3 million people in 2024—face some form of flood exposure (de Moel et al., 2011).

Due to its geography, the Netherlands developed one of the world's leading flood defense systems. The nation has established over 3700 km of water barriers. In addition to natural barriers such as dunes, there are approximately 1500 constructed barriers, including dikes, dams, weirs, and storm surge barriers (Bosker et al., 2019). Defense measures are not solely directed toward the coast, but also inland. Rivers are modified to dispose of water quickly and avoid silt-ups. Rivers are also strengthened by an advanced system of dikes and numerous floodplains that act as buffers to ensure safety at times of peak discharge. In addition to all this, the country has various pumping stations that allow for continuous water disposal and enable below sea-level living (van de Ven, 1993).

Despite all these protection measures, 100% safety cannot be assured. Water levels exceeding the rivers' and estuaries' water-bearing capacity can cause rivers to overflow. Moreover, dikes, pumps, and other water barriers are prone to human, technical, and mechanical failure (Danka & Zhang, 2015). A schematic overview of flood threats in the Netherlands is provided in Figure 1. Here, *A* presents flood exposure in unembanked areas. Although unembanked areas are mostly safe, elevated water levels—for example, due to storm surges—can cause these areas to inundate. *B* indicates flooding due to primary dike failure. Different forms of dike failure, like piping and breaches, can occur. Especially in extreme dike breach scenarios, large areas behind the dike can get flooded. *C* indicates flooding due to non-primary dike failure. The process is similar to primary dike failure. However, exposure tends to be smaller for areas protected by non-primary dikes, which protect against much smaller water bodies. *D* shows overflowing of regional surface water systems, also known as *fluvial* flooding. *E* indicates flood nuisance due to heavy precipitation, also known as *pluvial* flooding. *F* presents water nuisance due to high groundwater levels. In practice, flood zones can also overlap. Low-elevation coastal areas might, for example, enjoy protection from a primary dike to defend against inundation from the sea, while a secondary dike protects

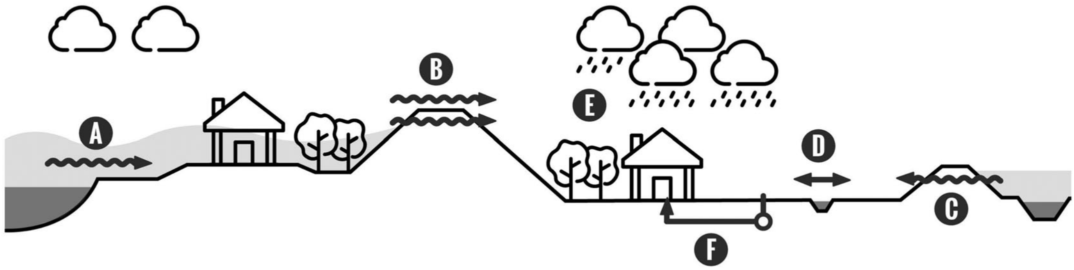


FIGURE 1 Causes of water nuisance and flooding in the Netherlands. *Note*: This figure presents flooding due to elevated water levels in unembanked areas (A); primary-dike defense failure (B); secondary-dike defense failure (C); overflowing of regional surface water systems (D); heavy precipitation (E); and elevated groundwater levels (F). Adapted from Ministry of Infrastructure and Water Management (2024).

against flooding from rivers in the hinterland. Since types *E* and *F* are considered water nuisance rather than flooding and are difficult to observe, we do not consider them in this study.

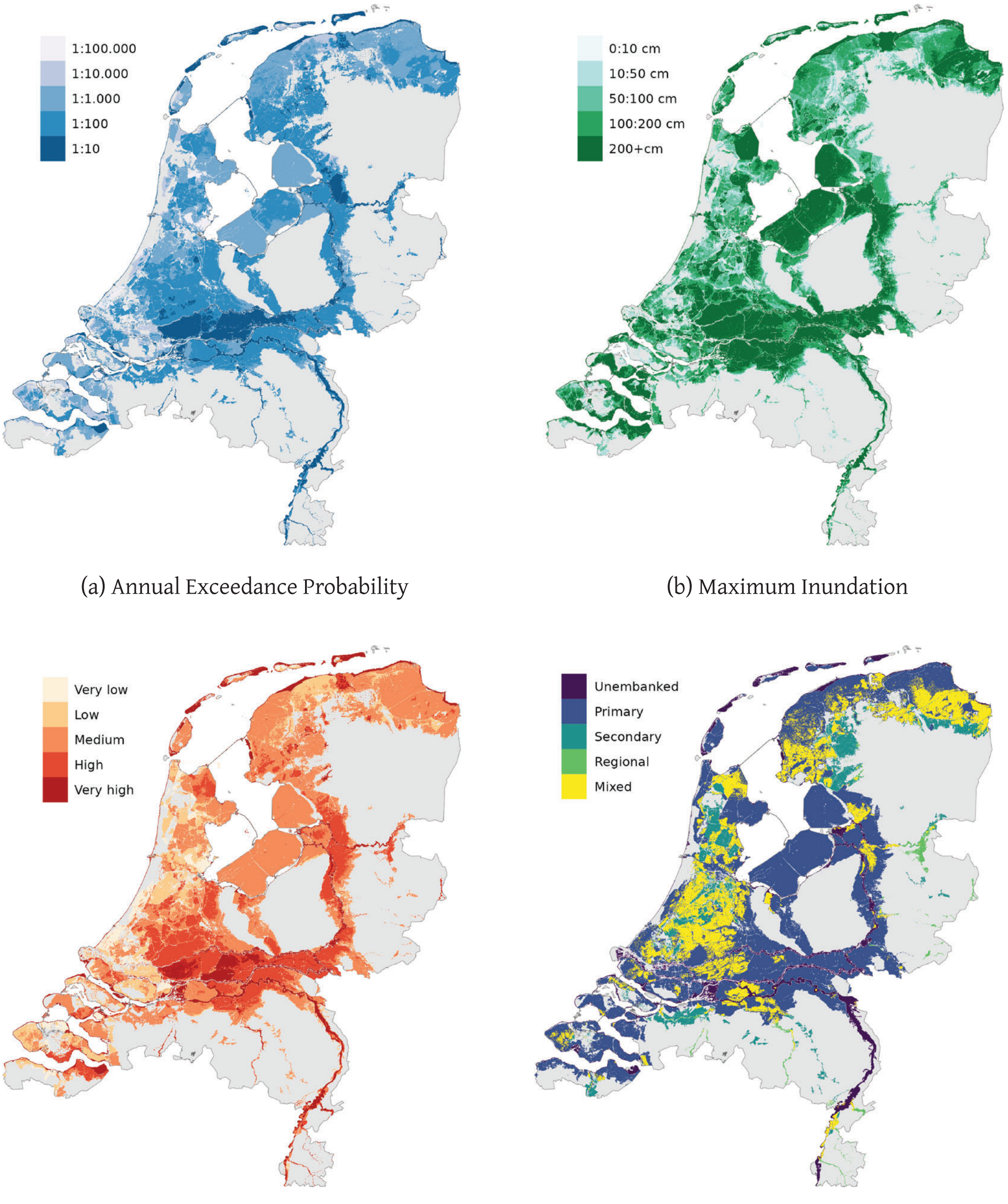
The spatial distribution of where these flood threats occur is presented in Figure 2. The flood maps in this figure are based on the aggregated results of numerous individual flood simulations.[2] Figure 2a indicates the odds that a flood will occur at a certain place in any given year. Figure 2b illustrates the aggregated maximum inundations. Figure 2c combines flood probabilities and maximum inundation into a single exposure measure based on the method of De Bruijn et al. (2015).[3] Since Figure 2c effectively combines exceedance probabilities and inundation into a single measure, this is also the main explanatory variable that we use in our empirical analysis.

The distinction between the different types of flood risk is shown in Figure 2d. Unembanked areas (corresponding with Figure 1, type A) are located along the coast, large lakes, and big rivers. Since most of the flood-prone areas are protected, unembanked areas cover only a small fraction of the country. The largest share of flood-prone areas is protected by primary barriers (corresponding with Figure 1, type B). These dikes protect against external water from the North Sea, Wadden Sea, major rivers, and lakes. Secondary dikes (corresponding with Figure 1, type C) protect against smaller water bodies, such as internal waters from lakes, smaller rivers, and canals, and are typically further away from the coast. Regional defense systems (corresponding with Figure 1, type D) are primarily located in the higher altitude parts of the country, in the East and South. The mixed flood zones indicate areas where different flood exposures overlap. The majority of overlap occurs between primary and secondary flood zones.

To interpret these flood maps, we note that they were developed for water engineering purposes. This entails that the models used to create the maps tend to incorporate some additional safety margins and can thus exaggerate actual risk levels. For example, 1 per 10 year events indicated in Figure 2a, occur much less frequently in reality. On the other hand, climate change is not taken into account in these maps. Hence, extremely small probabilities—such as 1 per 100,000 years—might adequately reflect current risk levels, but could underestimate future risk.

[2] Flood simulations are created with advanced hydrological models like Sobek and the GlobalFLoodRiskTool from water engineering companies Deltares and RoyalHasKoningDHV. The models use several inputs—like precipitation, soil types, elevation, and dike breaches—to estimate inundation levels and flood probabilities in specific scenarios (Leandro et al., 2009). Although the flood maps present exposure as of 2020, individual flood scenarios can be based on older data inputs.

[3] Flood hazards are calculated with individual scenario inputs rather than the aggregated results from Figure 2a and b, as different maximum inundations can occur at various flood probabilities.



(a) Annual Exceedance Probability

(b) Maximum Inundation

(c) Flood Damage Hazard

(d) Flood Zones

FIGURE 2 Dutch 2020 flood maps. *Note*: The flood maps present aggregated results of various individually modeled flood scenarios. While many of these scenarios overlap, they are not mutually exclusive. Therefore, aggregated results take the sum of probabilities (a); the most extreme inundation (b); and the sum of individual single-family house damage functions (see Figure A1) multiplied by the probability that a specific scenario will occur (c). See De Bruijn et al. (2015) for details. The input data for a–c is provided by Deltares—one of the world's leading water management research institutes and the primary Dutch government advisor on flood risk. The map in d is created using the maximum inundation flood zones per protection system. This data is publicly available at www.basisinformatie-overstromingen.nl
[Color figure can be viewed at wileyonlinelibrary.com]

While the maps are calibrated for risk in the year 2020, we believe they serve our purpose. The reason is that, while sea-level rise and more frequent extreme weather events increase the ceteris paribus likelihood of flooding, it is unlikely that they change Dutch flood zones (especially in the short run). These are predominantly determined by geographical features like elevation, proximity to water, catchment areas, and (natural) dikes. Consequently, present flood risk maps do not merely indicate current risk but also signal historic and future threats.[4]

3.2 | Collective water management

The Netherlands has a unique integrated water management approach, in which water governance is almost entirely in the hands of the government. Water-related responsibilities are determined by public law and executed by the national government, provinces, municipalities, and water boards. At the national government level, the Ministry of Infrastructure and Water Management is responsible for managing and maintaining the primary defense systems. It also issues warnings to other relevant government bodies when high water events are expected. Provinces are responsible for regional measures and have operational tasks, such as removing groundwater from the soil and managing the quality of the groundwater. Municipalities oversee groundwater in urban areas and handle the disposal of wastewater and rainwater via the sewage system. Water boards safeguard water quality within their districts and are responsible for maintaining secondary and regional flood defenses (Havekes et al., 2004).

Since the development and maintenance of the primary defense system is a responsibility of the national government, most of its funding comes from state funds.[5] This implies every taxpayer contributes to water defense and adaptation projects, regardless of whether individuals profit from them (or not) (Kaufmann et al., 2018). The national government budget for water management was 5.6 billion euros (0.5% of the GDP) in 2022 (Tweede Kamer der Staten-Generaal, 2023). Maintenance of secondary dikes and regional flood areas is the responsibility of water boards. These water boards are chosen through local elections and levy taxes within their operating area.[6] This allows them to operate independently from national politics. Because water boards spend tax revenues within the regions where they are collected, they are well placed to relate the costs of adaptation directly to the people who benefit from them. In 2023, waterboards collectively raised 3.5 billion (0.3% of the GDP) in taxes (CBS, 2023).

[4] Although it is unlikely that flood zones will change drastically in the short run, risk patterns may alter. For example, climate change affects fluvial flooding probabilities more rapidly than sea-level rise. Hence, we might expect more risk in the areas affected by this type of flood threat. Nevertheless, translating this to adapted flood maps proves to be difficult as it requires significant assumptions on climate change outcomes. Moreover, different types of flooding are not mutually exclusive but complementary. Higher sea water levels add to coastal flood risk but also affect river discharge. Therefore, it is challenging to isolate where and how much incremental risk is to be expected. Moreover, we would need to assume that markets make the same considerations as we do if we were to incorporate incremental climate change risk into our flood maps. Hence, we stick with a more straightforward approach. We consider the 2020 flood maps as a proxy for present and future risk and provide context on where incremental risk is to be expected.

[5] Exceptions exist for primary dikes that are managed by water boards. Maintenance costs for these dikes are paid for using a fixed distribution key. The government contributes 50%, the water boards collectively contribute 40%, and the water board where the reinforcement takes place contributes the remaining 10% (Löffler, 2022).

[6] Waterboard taxes differ per water board, but typically involve a fixed fee per resident (130-295 euros in 2025) plus a percentage of estimated property values (0.018%–0.077% in 2025) that is charged annually to homeowners.

If flood protection measures fail, the Calamities and Compensation Act stipulates that individuals should be compensated for property damage due to flooding. However, the specifics of the compensation are not clearly defined in the Act (De Vries, 1998). Moreover, the government is not liable for flood events not caused by failures of defense systems. Such floods can, for example, occur in unembanked areas that are located between water bodies and flood defense systems. Even though the government is not liable for these flood events, compensation has been provided in earlier events, potentially affecting individual expectations. Additionally, the law states that costs are only eligible for compensation if they are not reasonably insurable.

It is important to note that flood insurance in the Netherlands is not always available. Insurers distinguish their policies by flood type. Damages in unembanked areas or resulting from primary dike failures are never covered. This leaves relocation or private adaptation as the only option to avoid flood damage in these areas (Bosker et al., 2019). Damage as a consequence of secondary dike failure or regional flooding is covered by most insurers as part of the property insurance (Botzen & Van Den Bergh, 2008). Whether and how insurers differentiate their fees based on flood exposure levels is important, as it affects homeowners' costs of living. Unfortunately, such data is not publicly available.

3.3 | Individual adaptation

The Dutch flood defense system acts as a collective adaptation measure toward flood risk. Nevertheless, homeowners can mitigate risk at the individual level as well. Historically, this was done by building on elevated ground. With the introduction of collective dikes, such elevations were no longer necessary. However, if collective systems fail, private mitigation might still prove useful. Moreover, not all parts of the country are protected by dike systems. Floods are more likely to occur in unembanked zones or dry river beds. Since this risk is rather obvious, many houses in such zones are built in ways that mitigate flood damage.

3.4 | Risk perception and flood risk pricing

While the Netherlands is highly exposed to flood risk, actual flood events in embanked areas are rare—most areas are threatened by a "low probability, high impact" type of risk. The high level of adaptation enables people to live in places that are naturally unsuitable, such as areas below sea level. While these areas are well protected and dike failure probabilities are small, the impacts of a calamity in these areas can be disastrous, with potential inundation levels exceeding 5 m. A notable event that shaped collective flood risk awareness was the 1953 storm surge. During this event, multiple dikes breached, killing 1836 people.

In addition to historical risk awareness, climate change has sparked renewed interest in acceptable risk levels. However, there appears to be a mismatch between popular perceptions that worry about sea-level rise and flood engineers who warn of inland flood risk. According to flood experts, the most imminent threat in the Netherlands and other deltas is not coastal but comes from rivers. The reason for this is that, in contrast to long-term sea-level rise, weather patterns are already changing. Extreme precipitation and melting glaciers affect maximum discharge, putting more stress on the bearing capacity of the river and increasing dike erosion (Skougaard Kaspersen et al., 2017). Meanwhile, increasing winter precipitation can saturate soils, reducing dike stability and its propensity to handle erosion and piping, while drier summers add to dike deterioration through soil shrinking and cracking (Oude Essink et al., 2010; Schmocker & Hager, 2012; van der Wiel et al., 2024). A recent example where extreme precipitation led to flooding is the 2021 flash flood in the South of the Netherlands. These floods affected 2,500 houses, 5,000 inhabitants, and 600 businesses and resulted in a total of 400-500 million in direct physical and economic damage (Kok et al., 2023).

4 | EMPIRICAL MODEL

To identify the capitalization of flood-related risk, we employ an empirical design comparing the transaction prices of homes with varying flood risk exposure to unexposed homes. Flood risk depends on multiple factors, including the type of flood event, the probability of a flood, and the inundation when a flood happens. Since all components are related, we cannot assess them individually. Therefore, we follow an approach commonly used in the water risk management literature and the insurance industry, by measuring risk as flood hazard (Maranzoni et al., 2023). To assess the flood hazard per property, we overlay the transaction data with our flood hazard map (ratio values of Figure 2c). Since properties can overlap with multiple cells in our flood data, we calculate the mean weighted average risk per property, to obtain a single risk measure.[7] Moreover, we omit observations that are in both exposed and non-exposed grid cells, to limit the risk of false positives and negatives.

The flood maps in Figure 2 are rather granular, using 25-m^2 grid cells. Hence, they already account for most elevation changes at the local level. Nevertheless, considerable variety can occur within 25 m. For flood events where the maximum inundation is limited, such variations can be a driving factor in determining whether homes will be flooded. To account for within-grid cell exposure variation, we introduce a local elevation measure. We control for relative elevation by measuring the variation in absolute elevation using a 5-m ring around each property.[8] The intuition behind this measure is straightforward: if a property lies on a flat surface, the variation is zero. If a property is located on a hill or slope, the variation increases.

Proximity to water adds risk but also comes with positive amenity value (Bonetti et al., 2016; Jauregui et al., 2019; Mutlu et al., 2023; Simons & Saginor, 2006). We account for the "water amenity" by including water amenity fixed effects. In line with Bernstein et al. (2019), we consider distance bins to capture water views and access. The intuition is that those homes closest to the water enjoy both the view and accessibility. Homes further away mainly benefit from the accessibility element, but do not have the view. Moreover, the marginal benefits of water accessibility might be higher in close proximity, as it allows for access by foot.

Since not all water bodies are expected to be of equal amenity value, we distinguish between the sea, harbors, lakes, and rivers. We subdivide these water bodies by size. We classify rivers by width, taking 3, 6, 12, 50, and 125 m as cut-offs. Larger rivers provide different views than smaller rivers and also possess different amenity values, such as sailing possibilities. For lakes, we also create size classifications, using 100,000 m^2, 1 mln m^2, and 10 mln m^2 surface areas as cut-offs. Again, we expect varying amenity values from different types of lakes. Last, we split harbors into small and big harbors, using 10,000 m^2 surface area as the cut-off. Smaller harbors tend to be used for

[7] An alternative is taking the highest hazard value per property. However, this can lead to large exposure differences for adjacent properties if one happens to touch a flood raster cell while the other does not.

[8] The decision to use 5-m rings reflects the granularity of our elevation and flood data. Five meters is small enough to add additional information to our flood zone data and large enough to obtain reliable values.

recreational purposes while larger harbors—like the port of Rotterdam—also have a professional use with potential disamenities. Since access to different combinations of water bodies might yield unique benefits, we allow for the interaction of such combinations. Moreover, we interact the water accessibility combinations with districts to allow for spatial heterogeneity in water amenity premiums, for example, access to the same river might be valued more highly upstream than downstream due to pollution or a changing landscape.

We are also concerned about city amenity values indirectly shaped by flood exposure. Historically, cities developed in areas with access to relatively safe water bodies. For example, the oldest part of Amsterdam directly borders a large river but is also elevated. Due to the relationship between city development and flood exposure, we might accidentally capture amenity values associated with the historical center of a city rather than flood risk. We account for city-specific amenity values indirectly related to flood exposure through an "access to restaurant clusters" proxy. Restaurants rely on their location and concentrate in prime spots like market squares or the waterfront. As such, they also capture historical city amenity values. We distinguish between three cluster size classes—taking 5, 20, and 50 unique restaurant observations within that cluster as cut-offs—and consider restaurants part of a cluster if they are connected to other restaurants within a 50-m radius. We use distance to cluster bins of 0 to 1,000 m with 100-m intervals.

Using flood risk proxies that vary across space while controlling extensively for amenity value, we estimate the following equation:

$$\begin{aligned}\ln(Price)_{it} = {} & \beta_1 Exposed_i + \beta_2 Elevation + \beta_3 Exposed_i \times Elevation_i + \beta_4 BuildingVolume_i + \\ & \beta_5 ParcelSize_i + \beta_6 BuildingVolume_i \times ParcelSize_i + \gamma_i + \delta_{it} + \zeta_i + \eta_i + \epsilon_{pc6}, \quad (1)\end{aligned}$$

where $\ln(Price)_{it}$ contains the natural log of the transaction price of property i at year-quarter t; $Exposed$ is an indicator variable, equal to one if a property is in a flood zone; $Elevation$ is a continuous measure of local relative elevation; $BuildingVolume$ is a continuous measure of property size; $ParcelSize$ is a continuous measure of the parcel size; γ_i captures remaining hedonic characteristics through dwelling type by construction period by interior quality by exterior quality by monument status fixed effects; δ_{it} are year-quarter-by-district fixed effects that account for general market trends; ζ_i captures access to water amenities; and η_i captures the city center amenity value.

Our variable of interest is the flood exposure coefficient (*Exposed*). Since the relation between flood hazards and log home prices is not necessarily linear, we consider flood hazards in three ways. In our most basic model, we consider all properties with a flood hazard larger than 0 as exposed, and the remainder as unexposed. A second, more detailed specification classifies flood hazards into five categories. We take the cut-offs at 0, 0.0001, 0.001, 0.01, and 0.1 to create the following flood hazard categories: *unexposed*, *low hazard*, *medium hazard*, *high hazard*, and *very high hazard*. Following the flood hazard definition, properties with low exposure can expect annual damage of less than 0.001% of their building value. For properties with very high exposure, the expected annual damage is between 1% and 10% of the building value. The third, and most flexible specification, considers an exposure dummy combined with a continuous damage factor measure.

Exposure interacted with relative elevation (*Exposed* × *Elevation*) controls for highly local exposure variation unobserved in our flood exposure map. The interaction term distinguishes general elevation effects from those specific to properties in flood zones. We normalize scale elevation to have a mean of zero, for interpretation purposes. To account for any remaining location effects that might induce autocorrelation, we cluster our error term using PC6 dummies—PC6 areas correspond to the smallest ZIP codes with, on average, seven observations per zone.[9]

5 | DATA

The data comprises the flood maps in Figure 2, provided by Deltares and the National Water and Flood Information System, combined with five other sources: property transaction data from the Dutch Association of Real Estate Brokers and Valuers (NVM), property locations from the Basic Administration of Addresses and Buildings, water bodies from the Basic Registration of Topography, elevation records from the Current Altitude File of the Netherlands, and restaurant locations from OpenStreetMap (OSM). The property transactions in our data span from 1998 to 2023 and contain information on addresses, prices, dates, and structural characteristics. These present approximately 70% of the total Dutch residential transaction market and have been used in several studies (e.g., Aydin et al., 2020; Gaigné et al., 2022; Van Ommeren et al., 2011).

The Basic Administration of Addresses and Buildings is the official registrar of all addresses and buildings in the Netherlands. Their publicly accessible data contains additional property information such as the year of construction, purpose of use, plot surface, building shape, and location. Since this data offers addresses and exact location polygons, we use it to join transaction data with our spatial data. We match transactions with property locations by using the address as the common denominator.

The flood maps we use are the aggregated results of individual flood simulations that are publicly available on https://basisinformatie-overstromingen.nl. The aggregation is made by Deltares, following the procedure as in De Bruijn et al. (2015). Apart from serving as input to water management professionals, the flood maps serve as source layers for several public information platforms like www.klimaateffectatlas.nl , www.atlasleefomgeving.nl and www.overstroomik.nl. The large-scale professional use strengthens our confidence that these maps are technically relevant. Even more importantly, their integration with public information channels implies that individuals can access this information.[10]

We obtain water bodies from the land use database Basic Registration of Topography. The dataset is commonly used for applications in urban planning, environmental management, and infrastructure development. The water bodies in this dataset are derived from areal pictures and are highly accurate (0.1-m margin of error). In addition to providing the geographical scope of water bodies, several classifications are used to qualify these water bodies, for example, the name of the water body, whether it is part of the main river system and river width.[11] We associate these water bodies to our transaction data by measuring the euclidean distance from the property polygons to the nearest point of the respective water body.

[9] To address potential autocorrelation, at other spatial levels, we perform a robustness analysis where we cluster standard errors at PC5 and damage hazard grid levels. Results remain robust and are reported in Table A6.

[10] The semi-aggregated flood scenarios from the National Water and Flood Information System are also used by Bosker et al. (2019). The difference with flood maps used in their study and ours is that they consider maximum inundation and likelihood individually, whereas our map integrates them into a single measure of exposure. Nevertheless, underlying data remains the same and risk patterns are highly similar.

[11] The data from Basic Registration of Topography is used in various studies (e.g., Chang et al., 2023; Klompmaker et al., 2019).

We rely on elevation data from the Current Altitude File of the Netherlands to calculate our elevation profiles. The digital terrain model from this provider is highly detailed and covers the entire Netherlands. A limitation is that this data is not updated frequently. Moreover, the technologies for measuring elevation have changed over time. Therefore, we only consider the latest 2020–2022 update and treat elevation as fixed—an assumption that seems reasonable for most of our transactions, but might conceal variations over time. For efficient computing, we aggregate the raster cell sizes in this dataset to 1 by 1 m.

We obtain restaurant locations—which we use for the distance to restaurant cluster fixed effects—from OpenStreetMap. This is a collaborative, open-source geographic database that provides freely accessible and editable map data. Since we rely on clusters with at least five observations and only use these as control, we consider this publicly accessible data source adequate enough for our purpose.

By combining these data sources, we obtain a workable dataset. However, to get to our final sample we restrict the data through four more cleaning steps. First, we remove all transactions with any missing values. Second, we exclude outliers and dubious transactions. These include properties with extremely high prices (more than 2 mln) and low prices (less than 50,000); properties that are listed or sold multiple times on the same day; properties that are both listed and sold at the same day; properties that are relisted; transactions with different addresses but that sell on the same day in the same PC6 area for the same amount; properties that are sold within 5 days following a prior sale; and properties that are sold through alternative bidding processes like foreclosure auctions. Third, we remove all observations with contradicting flood exposure values, to ensure clear treatment and control buildings. Specifically, we drop observations that are not in any of the exposed flood zones from Figure 2d, but that do have a maximum inundation value, flood probability, or damage hazard assigned to them, and vice versa. Moreover, we omit observations at the exact boundary of a flood zone. Last, we remove observations where the elevation structure cannot be reasonably estimated. For the estimation of elevation structures, we use a threshold of at least 60 elevation grid cells per property.

Summary statistics of the final dataset are presented in Table 1. We observe that the average prices of unexposed properties are higher than those of exposed properties when located in unembanked and primary dike areas, while the opposite is true for regional flood zones. The average amount of days on the market follows an exact opposite pattern. On average, exposed properties in regional dike areas trade slightly faster than unexposed properties. However, this difference is very small. There are no substantial differences in building volumes and parcel sizes for exposed and unexposed zones in primary and regional dike areas. However, exposed properties seem to be larger and have bigger parcels than their unexposed comparables in the unembanked areas.

Exposed homes in unembanked areas tend to be located at higher absolute elevation levels. For the other areas, we observe an opposite pattern in which exposed properties are located at lower elevations. Moreover, we can observe larger relative elevation levels in unembanked areas, compared to the other zones. The maximum inundation is by far the highest in primary dike areas with an average of 1.68 m. On the other hand, unembanked areas are about six times as likely to experience flooding as primary dike areas. Regional dike areas tend to have low maximum inundations and flood probabilities. Consequently, these areas also face considerably lower average flood hazards than the other two areas.

Table A1 provides further details on property type and construction period. The property types in primary and regional areas tend to be rather similarly distributed. However, detached and semi-detached properties seem to be overrepresented in exposed unembanked areas. We observe no clear difference in terms of building quality or monument classification. However, there are con-

TABLE 1 Summary statistics.

Characteristic	Unembanked Unxposed N = 35,737	Unembanked Exposed N = 7,890	Primary Unxposed N = 185,328	Primary Exposed N = 386,363	Secondary Unexposed N = 133,803	Secondary Exposed N = 79,766	Regional Unexposed N = 44,639	Regional Exposed N = 3,513
Numeric—mean (SD)								
Price (×1,000)	283 (158)	262 (128)	308 (188)	270 (139)	284 (165)	287 (165)	267 (147)	270 (143)
Days on market	149 (236)	164 (260)	132 (226)	131 (222)	130 (216)	124 (202)	133 (218)	158 (251)
Volume (m^3)	432 (161)	458 (170)	409 (153)	399 (125)	404 (138)	396 (116)	432 (145)	441 (140)
Parcel (m^2)	247 (169)	273 (190)	220 (162)	217 (147)	228 (156)	216 (143)	239 (155)	289 (174)
Construction year	1,956 (44)	1,959 (46)	1949 (50)	1,971 (34)	1,962 (37)	1,974 (25)	1,957 (30)	1,972 (26)
Abs. elevation (m)	15 (16)	17 (14)	3.7 (6.8)	2.3 (4.2)	4 (7)	0 (6)	18 (21)	16 (15)
Rel. elevation (cm)	0.18 (0.24)	0.19 (0.23)	0.13 (0.17)	0.10 (0.11)	0.11 (0.12)	0.10 (0.10)	0.12 (0.15)	0.11 (0.15)
Inundation (m)	0.00 (0.00)	0.98 (0.75)	0.00 (0.00)	1.59 (1.03)	0.00 (0.00)	0.77 (0.69)	0.00 (0.00)	0.40 (0.36)
Flood prob. (‰)	0.00 (0.00)	13.77 (25.99)	0.00 (0.00)	2.85 (4.37)	0.00 (0.00)	0.78 (0.87)	0.00 (0.00)	9.55 (15.84)
Flood hazard (×1,000)	0.00 (0.00)	1.77 (3.99)	0.00 (0.00)	1.23 (2.75)	0.00 (0.00)	0.10 (0.13)	0.00 (0.00)	0.94 (1.78)
Categorical—%								
< 200 m								
River: <6 m	28	30	44	56	56	63	25	47
River: 6–50 m	31	31	54	66	66	82	29	71
River: >50 m	10	25	5.4	4.2	4.3	3.1	1.0	1.0
Lake: <1 mln m^2	20	33	28	31	32	35	24	38
Lake: 1–10 mln m^2	1.7	1.9	3.0	4.5	4.2	5.9	2.1	2.1
Lake: >10 mln m^2	4.2	1.1	1.8	1.2	1.7	2.3	0.5	0.7
Harbor: <100k m^2	0.9	2.5	1.1	0.6	1.0	1.0	0.6	<0.1
Harbor: >100k m^2	7.1	12	3.4	1.3	1.3	0.5	0.8	0.9
Sea	<0.1	<0.1	<0.1	<0.1	<0.1	0	0	0

Note: This table presents the summary statistics of the data. To derive meaningful comparisons between exposed and unexposed properties, we group the data per flood zone and include only those properties where exposed observations lie within 1,000 from an unexposed observation and vice versa. Since unexposed properties are not linked to flood zones directly, we relate a flood type to them (using the flood type of the property that they match). Because unexposed properties can be close to multiple flood types, single values can show in multiple columns. An overview of the complete dataset is provided in the Appendix.

TABLE 2 Flood exposure price effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposed	−0.012***	−0.013***	−0.013***	−0.014***	−0.013***	−0.011***	−0.009***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Damage factor	−0.460	−0.644	−2.411***	−2.260***	−1.831**	−2.057**	−2.185**
	(0.426)	(0.423)	(0.599)	(0.590)	(0.622)	(0.661)	(0.812)
RelElev		−0.002***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
		(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Exposed × RelElev		0.005***	0.004***	0.004***	0.003***	0.004***	0.005***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.932	0.932	0.949	0.954	0.955	0.957	0.962
R^2 adj.	0.922	0.922	0.931	0.936	0.937	0.938	0.940
Num.obs.	1,781,698	1,781,698	1,781,698	1,781,698	984,985	898,485	667,389
Hedonics	X	X	X	X	X	X	X
YrQtr × district	X	X	X	X	X	X	X
Water amenity			X	X	X	X	X
City amenity				X	X	X	X
BDA cut-off					<1,000 m	<500 m	<200 m
Exposure variation					District	District	District

Note: This table presents ordinary least squares estimates, where the dependent variable is Ln(*Price*). Exposed is a dummy variable that equals one for a property exposed to flood risk. Damage factor is a measure of flood exposure ranging from 0 to 0.06. Elevation is the standard deviation of 0.5-m elevation grids surrounding a property in a 5-m buffer. Hedonics accounts for property-specific characteristics through property volume, parcel size, and property volume × parcel size control variables and property type × construction period × inside quality × outside quality × monument fixed effects. YrQtr × District accounts for year quarter × district fixed effects. Water amenity accounts for water accessibility. Column 1 estimates exposure effects using our entire data sample, only controlling for hedonic characteristics and general district price developments. Column 2 introduces local elevation. Column 3 adds water amenity fixed effects. Column 4 adds city amenity fixed effects. In Columns 5 to 7, we restrict our data following the border discontinuity analysis approach using 1,000-, 500-, and 200-m cut-offs. Here, we also omit observations in districts with no variation in exposure classes. *T*-statistics based on standard errors clustered at the six-digit postal code level are presented below the coefficients. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.

struction periods in which relatively many properties are built in unsafe areas. Especially the period 1981–1990 stands out here.

6 | RESULTS

6.1 | Baseline results

Table 2 presents general price effect estimates from flood risk exposure.[12] The dependent variable is the natural log of the transaction price. We consider four independent variables that collectively present flood risk exposure. "Exposed" is a flood risk dummy with a value of one if a property is exposed to any level of flood risk. "Damage factor" also measures flood risk, but consists of a continuous measure, indicating the level of risk. Since "exposed" and "damage factor" both

[12] We also examine liquidity effects in Table A5 but do not find robust significant results.

measure risk, they are mutually dependent. We choose to consider both measures simultaneously, as this model specification seems to fit the data most appropriately, while still providing credible results (alternative models are presented in Tables A3 and A4). Besides the direct measures of risk, we account for risk exposure variation through "elevation". This is a continuous measure indicating the variance in absolute elevation in a 5-m buffer surrounding a property. The elevation-by-exposed interaction disentangles general elevation effects from those effects specific to flood risk-exposed properties.

In Column 1, we control for property characteristics. Moreover, we consider time-varying location characteristics and price developments through year-quarter-times-district fixed effects. In this baseline analysis, flood exposure decreases property prices by 1.2% or 3,325 euros at the point of means. No significant differentiation following the extent of exposure can be observed. In Column 2, we account for property-specific adaptation through elevation. With a value of 1.7%, the general exposure coefficient becomes considerably stronger, suggesting that there is indeed substantial variation in flood risk exposure that is not captured by the coarse flood exposure maps. Notably, the coefficient for elevation is negative and significant, indicating that home buyers generally prefer homes on flat terrain. However, this effect is offset when properties are exposed to flooding. For these properties, being located on a slope or uneven terrain is positive, as it reduces exposure. The magnitude of the elevation effect is considerable. A one standard deviation increase in elevation mitigates negative price effects from flood exposure by (−0.002 + 0.005) = 0.3%. In Column 3, we further account for water amenities. While the exposure dummy effect remains stable, the continuous risk measure now also becomes significant. At the median damage factor level of exposed properties in our dataset, the additional effect is only modest. With a value of 0.00033, the marginal damage factor price effect is less than 0.1%. However, in the tails of the risk distribution, effects become much stronger. At the 95th percentile, the marginal damage hazard effect is 1.0%, at the 99th percentile, it is 2.4%, and at the 99.9th percentile, the effect is 7.7%. Together with the 1.3% from the exposure dummy, this results in a total flood risk discount of 9% for those properties that are most exposed.

Column 4 extends the water amenity fixed effects with distance-to-city amenities. This does not change the exposure coefficient meaningfully, alleviating concerns about the price effect being driven by historical city amenities.

Although our model specification is quite strict, unobserved structural characteristics might bias the results. Hence, we gradually restrict our data in Columns 5 to 7. We do so by implementing a border discontinuity approach as described by Bosker et al. (2019). This data restriction assures that we compare properties with similar location characteristics, but comes at the trade-off of losing observations. A tighter cut-off point provides more comparable homes in terms of location characteristics, but also reduces the degrees of freedom available to estimate coefficients. A second restriction is that we only focus on districts that contain exposed and unexposed observations.

In Column 5, we use a cut-off of 1,000 m, so that the data only contains properties less than 1 km away from a flood border. This omits about half of our observations. The fact that our sample remains rather large despite this restriction illustrates that most Dutch homes are clustered in areas close to water. This first data restriction slightly reduces the strength of the coefficients, but the results remain robust. In Columns 6 and 7, we further tighten our model by using 500- and 200-m cut-offs. Again, the results remain robust. Applying our most restrictive model estimates to the complete dataset provides an average flood risk discount of 1.1%, with an upper bound of 7.8% at the 99.9th percentile. The observed price effects are both statistically and economically significant, with an average absolute price effect of 2,969 for exposed properties.

6.2 | Heterogeneous effects

6.2.1 | Flood types

The previous results highlight average flood risk discounts on the housing market. However, discounts may vary across flood zones due to differing institutional settings and unobserved variation in exposure. To address this, we examine price effects across unembanked, primary-dike, secondary-dike, regional, and mixed flood zones (as in Figure 2d).

Unembanked areas are physically and financially unprotected. In these areas, flood risk exposure tends to be high, and no insurance or disaster compensation is provided. In primary dike zones, insurance is not offered either, but here homeowners are entitled to (partial) disaster compensation. These areas are well protected but also face significant inundation if a disaster happens. The "low probability, high impact" type of risk in these areas is overall lower than in unembanked areas, but higher than for the remaining flood zones. Moreover, inundation in these areas would be long-lasting. In secondary dike flood zones and regional flood areas, flood risk tends to be low due to limited inundation and rather low probabilities. Also, insurance is provided in these areas. Because of insurance availability, owners are formally not entitled to disaster compensation.

To estimate the effect of flood risk exposure per flood type, we replace the "exposed" dummy with flood zone categories using "no exposure" as the reference. Again, we include a continuous damage factor measure. We allow this measure to vary across zones by interacting it with the zone categories. Moreover, we include a standalone elevation measure, plus one that interacts with flood exposure. We allow variation across flood zones here as well by using an elevation-by-flood-type interaction term.

The results of this new model specification are presented in Table 3. Column 1 shows the flood exposure price effects per category, without accounting for the amount of risk within each category. As expected, we can observe that the discounts are strongest in unembanked areas with an average price discount of 3.3%. Effects are considerably smaller, but still significant in primary, secondary, and mixed flood zones, with averages of 1.6%, 1.0%, and 1.6%, respectively. We do not observe price discounts in regional flood zones.

The significant difference in the magnitude of discounts across flood zones suggests that physical and financial adaptation measures seem to matter. Although we can not observe what the discounts in protected areas would have been without such measures, they are likely to equal or even exceed those observed in unembanked areas. Primary and secondary areas are naturally more exposed to flood risk than unembanked areas due to their (lack of) elevation. Many of these areas would even be permanently inundated without adaptation measures, as can be observed in land reclamation maps.

Discounts in primary dike areas remain present, despite homeowners' entitlement to disaster compensation in these flood zones. The fact that we still observe a considerable discount suggests that people are unaware of this compensation or consider it insufficient to offset all costs. (This seems a fair assessment. Besides limited coverage, disaster compensation is prone to political decisions, and there is no guarantee that properties will remain covered in the future.)

Remarkably, we observe no flood risk discount in regional flood areas. Two possible explanations are limited risk awareness and the insurance setting. In contrast to unembanked areas and

TABLE 3 Heterogeneity by flood zone.

	(1)	(2)	(3)	(4)	(5)	(6)
Unembanked	−0.033***	−0.036***	−0.036***	−0.031***	−0.033***	−0.032***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Primary	−0.016***	−0.016***	−0.016***	−0.012***	−0.012***	−0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Secondary	−0.010***	−0.009**	−0.009**	−0.007**	−0.006*	−0.006*
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Regional	0.008	0.009	0.009	0.009	0.009	0.010
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Mixed	−0.016***	−0.010***	−0.010***	−0.013***	−0.007**	−0.007**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Unembanked × damage factor		2.113	2.319		1.773	2.000
		(1.795)	(1.873)		(1.816)	(1.889)
Primary × damage factor		−2.393***	−2.477***		−2.230**	−2.333**
		(0.645)	(0.644)		(0.745)	(0.744)
Secondary × damage factor		14.351	13.347		11.329	10.187
		(11.483)	(11.433)		(12.078)	(12.050)
Regional × damage factor		−1.436	−1.772		0.260	−0.182
		(3.635)	(3.719)		(3.642)	(3.729)
Mixed × damage factor		−6.849***	−6.836***		−7.978***	−8.035***
		(1.360)	(1.357)		(1.686)	(1.684)
Elevation			−0.003***			−0.003***
			(0.000)			(0.001)
Unembanked × elevation			0.000			0.000
			(0.002)			(0.002)
Primary × elevation			0.004***			0.004***
			(0.001)			(0.001)
Secondary × elevation			0.005***			0.006*
			(0.002)			(0.002)
Regional × elevation			0.005			0.008
			(0.006)			(0.007)
Mixed × elevation			0.006***			0.006***
			(0.001)			(0.002)
R^2	0.954	0.954	0.954	0.957	0.957	0.957
R^2 adj.	0.936	0.936	0.936	0.938	0.938	0.938
Num.obs.	1,781,698	1,781,698	1,781,698	898,485	898,485	898,485
Hedonics	X	X	X	X	X	X
YrQtr × district	X	X	X	X	X	X
Water amenity	X	X	X	X	X	X
City center	X	X	X	X	X	X
BDA cut-off				<500 m	<500 m	<500 m
Exposure variation				District	District	District

(Continues)

TABLE 3 (Continued)

Note: This table presents ordinary least squares estimates, where the dependent variable is Ln(*Price*). We consider five flood exposure zones with a sixth unexposed zone as a reference. Damage factor is a continuous measure of flood risk ranging between 0 and 0.06. The interaction with flood zones identifies marginal exposure effects per flood zone. Elevation is the standard deviation of 1-m grids surrounding a property in a 5-m radius. Again, we include an interaction term with flood zones to account for marginal exposure. Columns 1 to 3 estimate effects for the entire data sample. Columns 4 to 6 estimate the same effects on a restricted sample. *T*-statistics based on standard errors that are clustered at the six-digit postal code level are presented below the coefficients. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.

zones protected by large dikes, flood risk in regional areas is likely to be less salient. People might be unaware of the risk and therefore not require compensation in the form of a lower house price. Alternatively, people might be aware of the risk, but not of the costs. In the Netherlands, flood insurance is not a stand-alone product, but part of an overall home and contents insurance bundle. The fact that insurance fees entail multiple types of risk can mask individual pricing signals. It is also unclear to what extent insurers differentiate their fees based on flood risk exposure of the home. If insurance fees do not clearly distinguish between individual exposure levels, the absence of flood risk discounts in regional flood zones could even be rational.

A natural question is whether the differences in observed discounts across flood zones are driven by physical adaptation measures that reduce damage hazard levels, or by institutional measures that lower ownership risk. We try to disentangle these effects in Columns 2 and 3 by controlling for the amount of exposure and elevation in any of the given zones. Examining the flood zone category coefficients, we observe that the effects become slightly stronger but remain stable overall. This stability suggests that flood exposure price effects are largely driven by an extensive margin of being located in a specific flood zone, regardless of the exact exposure within that zone. For primary, secondary, and mixed flood zones, we observe an additional price effect that is driven by exposure intensity. This intensive margin effect is significant for the damage hazard and elevation measure in the case of primary and mixed areas. For secondary areas, only the elevation measure is significant. Applying the estimated coefficients to our entire data sample shows median flood exposure price effects of 3.4%, 1.9%, 0.8%, and 1.7% for unembanked, primary, secondary, and mixed areas, respectively. The results remain robust in Columns 4 to 6 where we apply the same steps, but using the border discontinuity design.

6.2.2 | Temporal effects

The previous analyses considered price effects from flood risk as fixed. However, this assumption may be invalid due to increased risk awareness and actual incremental risk caused by climate change. At the same time, ongoing efforts have been made to mitigate flood risk in the Netherlands. Although these adaptation programs do not fundamentally alter exposure zones, they may affect observed damage factors. To identify temporal variation, we adapt our main model by adding an exposure-by-time variable. Here, time presents the difference in days between the transaction of interest and the first transaction date in our observations, scaled to a value between 0 and 1. We do not account for the level of exposure within a zone. To assess temporal variation by flood zone while limiting the number of coefficients to be interpreted, we fit our model to different subsets.

Results are presented in Table 4. Column 1 shows temporal effects across all flood zones. The exposed coefficient is negative and significant, suggesting that flood risk already affected property prices in 1998. However, this price effect has become stronger over time. The exposure-by-time

TABLE 4 Heterogeneity by transaction date.

	(1)	(2)	(3)	(4)	(5)	(6)
Exposed	−0.008***	−0.037***	−0.010***	−0.002	0.028**	0.010
	(0.002)	(0.009)	(0.003)	(0.004)	(0.009)	(0.007)
Exposed × time	−0.008**	0.006	−0.004	−0.003	−0.031**	−0.027***
	(0.003)	(0.012)	(0.004)	(0.006)	(0.012)	(0.008)
Elevation	−0.003***	−0.008**	−0.002**	−0.003*	−0.008***	0.003
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
Exposed × elevation	0.004***	0.000	0.003**	0.006**	0.016*	−0.001
	(0.001)	(0.006)	(0.001)	(0.002)	(0.007)	(0.002)
R^2	0.957	0.953	0.959	0.961	0.947	0.966
R^2 adj.	0.938	0.913	0.938	0.940	0.927	0.943
Num.obs.	898,485	46,470	564,730	208,297	50,150	203,119
Hedonics	X	X	X	X	X	X
YrQtr × district	X	X	X	X	X	X
Water amenity	X	X	X	X	X	X
City center	X	X	X	X	X	X
Zone	All	Unembanked	Primary	Secondary	Regional	Mixed
BDA cut-off	<500 m	<500 m	<500 m	<500 m	<500 m	<500 m
Exposure variation	District	District	District	District	District	District

Note: This table presents OLS estimates with Ln(*Price*) as the dependent variable. Exposed is a dummy with a value of one if a property is exposed to flood risk and zero otherwise. Time measures the number of days passed since the beginning of our sample in January 1998, scaled to a value between zero and one. Elevation is the standard deviation of 1-m grids surrounding a property in a 5-m radius. Column 1 estimates average effects across all flood zones. Columns 2 to 6 estimate effects for individual flood zones. Unexposed reference properties are included in all models. *T*-statistics, based on standard errors clustered at the six-digit postal code level, are shown below the coefficients. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.

interaction term has a significantly negative value of 0.008, indicating that average exposure price effects rose from 0.8% to 1.6% between 1998 and 2023.

The data split across flood zones in Columns 2 to 6 shows that temporal effects are mostly driven by transactions in regional and mixed flood areas. Notably, we can observe a positive price effect from flood exposure in regional areas. This likely suggests that our model fails to capture some of the positive water amenities, even with the many controls included in the models. Despite this unexpected exposure premium, we can observe a strong negative time effect in regional flood zones. The growing discount in regional flood areas suggests growing awareness of flood exposure in this specific zone.

6.2.3 | Buyer sophistication

In addition to understanding how flood risk capitalization develops over time, we are interested in heterogeneity across market segments. In a key study, Bernstein et al. (2019) show that price effects from sea-level rise exposure are driven by well-informed buyers. As a proxy for sophistication, they consider the non-owner-occupied segment of the market.

We follow an alternative approach to estimate a similar "sophistication effect." As a proxy for sophistication, we consider property price ranges. Buying in the top market segment requires wealth, which is related to income and education (Card, 1999). Moreover, wealthy individuals have a larger range of choices and can be more selective in their buying decisions. To avoid mechanical bias from using the observed transaction prices, we classify our own market segments through a simple hedonic model. We predict prices based on property characteristics, the transaction year, and the municipality. We do not account for more precise location characteristics, as these might be related to our variable of interest. After estimating building values, we classify market segments based on whether or not a property belongs in the upper or lower half of the estimated price distribution in any given neighborhood and year.

Our sophistication proxy has a benefit over the non-owner occupier proxy that is relevant in our empirical setup. In contrast to the market examined by Bernstein et al. (2019), listed properties in the Netherlands tend to receive multiple bids. If unsophisticated buyers consistently outbid sophisticated buyers—because they do not price in flood exposure—we cannot observe sophisticated buyer bids. The unsophisticated buyers in our proxy are unlikely to participate in the upper market segment—as this is above their budget. Hence, we can observe the “true” sophisticated buyer price preferences by focusing on the upper half of the price distribution.[13]

We expect the heterogeneity in price effects by sophistication to be mainly driven by the information channel. In the context of our empirical setup, we do not expect transactions classified as “sophisticated” to be part of the buy-to-let segment. The reason is that we analyze single-family homes, while investors typically operate in the multifamily segment. Moreover, we exclude nonstandard transactions such as auctions. Again, these are more likely to be bought up by investors. Hence, we expect “sophisticated” transactions to be mainly for consumption.

Results are presented in Table 5. Each model indicates the triple interaction between an exposure dummy, the transaction period, and the price segment. In Column 1, we use our entire dataset, and in Columns 2 and 3, we apply the border discontinuity restriction. In line with previous results, we account for hedonic characteristics, water amenities, year-quarter-by-district fixed effects, relative elevation, and its interaction with exposure. Although we can observe significant price effects in both market segments, the effects appear consistently stronger for the upper segment. The large price effects for this more sophisticated market segment suggest that well-informed buyers indeed (mostly) drive the observed price effect.

Notably, the spread between price effects is strongest in Column 3, where we focus on the borders of the flood zones. It is indeed more difficult to distinguish safe from unsafe properties when they are close to another. We also observe that the spread in risk pricing becomes smaller over time. This suggests that unsophisticated buyers are catching up—access to flood information has indeed become more accessible. Through websites like www.overstroomik.nl (introduced in 2014), home buyers can easily assess whether a property is exposed to flood risk by entering an address. Moreover, climate change awareness has reached a broader public as scientific information has spread through more mainstream channels. Also, by now, an increase in national and international disasters has made environmental risk more salient. A prime example of this is the 2021 flooding in a regional flood zone in the South of the country, which received national publicity.

[13] Unfortunately, isolating the price preferences of the unsophisticated market segment is more difficult as sophisticated buyers still have access to this part of the market.

TABLE 5 Heterogeneity by time and sophistication.

	(1) Market segment =		(2) Market segment =		(3) Market segment =	
	Bottom	Top	Bottom	Top	Bottom	Top
Exposed × 1998:2007	−0.010***	−0.014***	−0.005*	−0.013***	−0.002	−0.006*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Exposed × 2007:2016	−0.013***	−0.016***	−0.005*	−0.016***	−0.000	−0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Exposed × 2016:2023	−0.017***	−0.020***	−0.012***	−0.017***	−0.010***	−0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
R^2	0.953		0.957		0.968	
R^2 adj.	0.936		0.938		0.941	
Num.obs.	1,744,582		880,092		442,578	
YrQtr × district	X		X		X	
Elevation × exposed	X		X		X	
Water amenity	X		X		X	
City amenity	X		X		X	
BDA cut-off			<500 m		<100 m	
Exposure variation			District		District	

Note: This table presents OLS estimates with Ln(*Price*) as the dependent variable. The key coefficient is a triple interaction of exposed × market segment × transaction period. Market segments are based on the upper and lower halves of estimated price distributions per neighborhood and transaction year. We follow our main model specification and control for non-interacted market segments. Model 1 report estimates for the entire dataset, and models 2 and 3 report estimates for restricted samples. *T*-statistics, based on standard errors clustered at the six-digit postal code level, are shown below the coefficients. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.

7 | DISCUSSION AND CONCLUSION

7.1 | Economic impact

To translate our microeconomic findings into macroeconomic implications, we apply the estimated discounts to all single-family residential properties in the Netherlands. This should provide a general overview of how much the "market" is prepared to spend to mitigate flood risk entirely. Beyond predicting absolute value loss, we estimate marginal value loss that has materialized in the last two decades. We also estimate the total all-else-equal price effect of two counterfactual scenarios. In the first scenario, we assume increased risk salience. In the second scenario, we consider the Netherlands without adaptation measures in place. These scenarios should provide policy-makers and institutions with an indication of potential future developments. Moreover, they enable us to evaluate the benefits of adaptation.

To obtain a macroeconomic estimate, we use our residential transaction data to estimate the market values of all single-family properties in the Netherlands. Specifically, we fit the transaction data to the following simplified hedonic model:

$$Ln(Price)_{it} = \alpha + \beta_1 V + \gamma_y + \eta_{tl} + \epsilon \tag{2}$$

TABLE 6 Macroeconomic value loss due to flood risk exposure.

	Total value exposed	Real value lost	Temporal effects	Growing salience	No more dikes
Unembanked	22.73	0.74	0.00	0.11	0.75
Primary	744.42	10.82	0.00	2.08	233.66
Secondary	113.28	0.71	0.00	0.12	92.09
Regional	5.59	0.00	0.17	0.00	0.27
Mixed	213.57	3.11	5.68	0.54	157.57
Total	**1099.59**	**15.37**	**5.86**	**2.86**	**484.34**

Note: This table presents aggregated flood exposure price effects (in billion) for five all-else-equal scenarios. *Total value exposed* estimates the total value of all 2022 properties that face any flood risk. *Real value lost* estimates realized value losses, using significant coefficients from Table 3, Column 3 as inputs. *Temporal effects* estimates the price effects from altering risk levels and increasing climate awareness. Estimates are based on significant exposure by time coefficients from Table 4, using a value of 1 for the time variable. *Growing salience* estimates total discounts for a scenario where the entire market is "sophisticated." To estimate this scenario, we take the "real value lost" discounts but multiply them by 1.3 if the property belongs to the top market segment and by 0.769 if it belongs to the bottom market segment. The multiplication roughly represents the discount spread from Table 5. To retrieve the final estimates, we subtract the estimated value from the predictions where all properties are classified as belonging to the top market segment. *No more dikes* presents total value loss estimates for a scenario without flood adaptation. To estimate this scenario, we apply the significant unembanked discount rates from Table 3, Column 6 to all exposed properties. Moreover, we make an assumption that all properties below the average sea level (NAP < 0) will be permanently inundated without protective measures. Ignoring any option value for future land reclamation, we write these properties completely off.

in which α is a constant intercept; V is building floor surface; γ_y are construction period fixed effects; η_{tl} are year-by-municipality fixed effects; and ϵ is the error term. The fitted model is used for out-of-sample predictions on the entire Dutch single-family residential housing stock as of 2022—using the Basic Administration of Addresses and Buildings as baseline.

Using the same approach as in our empirical design, we associate each property with flood hazard levels, flood zones, and relative elevation values. We estimate a flood risk discount for each property by applying the relevant values to the coefficients that we estimated in our empirical analysis. Multiplying the estimated flood risk discount by the predicted property value yields an absolute estimated loss per property. The sum of losses is the estimated national cost of flood risk for the entire Dutch residential housing market. This approach might underestimate/overestimate actual value losses in two ways. First, the simplified hedonic model estimates property prices rather crudely. If properties with flood exposure indeed have structurally higher water amenity values, their prices might be underestimated. Second, we do not account for all types of pricing heterogeneity. While this might bias estimates for individual properties, variation should be balanced out for the sum of estimates.

The results of this prediction exercise are presented in Table 6. The first column shows the total value at risk. This is the sum of all estimated property values —as of 2022—that are exposed to any degree of flood risk. For all flood zones together, the estimated exposed value is about 1.1 trillion. The majority of this is driven by homes located in primary embanked areas. Column 2 estimates the realized expected value loss caused by flood risk exposure. While discount levels in unembanked areas are relatively high, these areas are not densely populated, and thus, overall value loss remains limited at 0.74 billion. By far the largest part of the estimated loss stems from primary embanked areas. While average discount rates in this area are relatively low (1.4%) compared to those in unembanked areas (3.4%), the amount of exposed properties is far larger. The total exposure in secondary areas is, with a value of 0.71 billion, around the same order of magnitude as unembanked areas. Even more than in the case of primary dikes, this is mainly driven by the quantity of exposure, as average estimated discounts are only 0.6%. We observed no significant discount in regional areas, so this value is by definition zero. We estimate a total realized value loss of 3.11 billion in mixed areas, with an average discount of 1.3%.

Column 3 estimates the net effect of rising climate awareness and altering risk (perceptions) levels. During a period of more than two decades, the total marginal value loss is estimated at 5.86 billion. In Column 4, we estimate the additional price effects in a scenario where every home-owner demands discounts equivalent to those observed for the "sophisticated" buyers group. We estimate that a rise in risk awareness will result in a 2.86 billion value loss. Notably, additional losses are limited as they involve discounts on properties with relatively low values to begin with. Column 5 estimates the price effects of an extreme scenario without flood defenses and financial protection measures. The total estimated value loss in this is a staggering 484 billion.[14] While absolute value loss remains the strongest in primary embanked areas, secondary dike and mixed areas face the strongest relative decline in this scenario.

These macroeconomic estimations highlight a huge gap between potential and realized value losses. Foregoing protection measures today results in an estimated loss of almost 0.5 trillion. However, through continuous investments in collective adaptation, this loss has been limited to "only" 18.3 billion ($15.37 + 0.5 \times 5.86$). Notably, this gap is not driven by a lack of risk salience or climate awareness, as limited salience levels only account for around 3 billion.

To evaluate whether the adaptation benefits are worth the investments, we also need to consider the cost of adaptation. In total, the Dutch national government and water boards collect and spend around 9.1 billion on water management, annually. At the current Dutch 10-year bond yields of 2.8%, this represents a present value of some 325 billion. The benefits of collective adaptation thus exceed the costs by far, with a positive NPV of around 141 billion. Notably, the benefits from collective adaptation are likely even larger as it also protects assets other than single-family homes, which are not considered here. (And of course, the damages in case of flooding without adaptation would be a multitude larger if second-order effects are considered.)

7.2 | Conclusion

This article studies flood risk pricing in the Dutch housing market. The Dutch setting is important and representative, with different types of flood risk that are typical for a river delta. In contrast to other types of coastal areas, river deltas face a joint flood threat from both rivers and the sea. Especially in light of climate change, the joint effect from these two systems is relevant, as river systems are affected more rapidly. At the same time, the Netherlands is a country that is highly adapted to flood threats, investing significantly in waterworks such as dikes and levees.

We find evidence of house price discounts based on flood risk exposure—on average, properties prone to flooding trade at a 1.1% discount, compared to unexposed properties. Discounts become stronger as flood risk exposure increases, but are also largely driven by financial exposure. We observe larger discounts in market segments that are most accessible to sophisticated buyers, suggesting a difference in flood risk salience among private consumers. Notably, this gap converges over time as information becomes more easily accessible. Our collective results suggest that the Dutch housing market incorporates flood exposure, at least to some degree, in property prices.

[14] This value loss will likely coincide with appreciating property values in non-exposed areas, due to a total reduction of housing supply.

The presence of a flood exposure discount contrasts with popular views that warn of consumer unawareness and potential price shocks as it relates to flood risk (Bani et al., 2024; OECD, 2014). Indeed, the observation that housing market participants consider flood risk exposure alleviates concerns about sudden price shocks related to flood risk exposure, which may potentially cause large welfare redistribution. However, we observe that flood risk discounts are changing over time—this development, where discounts become higher, is negative for exposed homeowners, but prospective buyers enjoy compensation for potential future damages. Moreover, changes in discounts are modest. During an approximately 20-year period, flood risk discounts changed no more than 5%. Considering the average nominal annual growth in housing prices of 5.6% over the past 30 years (CBS, 2025), this relative price decline is unlikely to cause substantial macroeconomic effects, for example, through "underwater" mortgages or significant declines in household wealth.

Our results align with previous studies that also identify a flood exposure discount. For example, we can compare our results with the work of Bosker et al. (2019) and Mutlu et al. (2023). The former identifies residential price discounts of 1% in primary dike exposure zones. Our 1.9% discount for equal flood zone exposure is considerably higher. We attribute the difference in magnitude to our more detailed approach in measuring flood risk exposure and prices, which we assess at the property level, rather than at the level of 6-digit postal code areas. Moreover, our dataset contains more recent property transactions. Given that we observe an upward-sloping exposure effects, using more recent data leads to an increase in the average effect. The study of Mutlu et al. (2023) identifies a 5.6% pre-flood event discount in an unembanked, high-exposure area between 1990 and 1993. This discount is within the range of price effects that we observe for highly exposed properties.

Compared to sea-level rise discounts observed in the United States, the price effects observed in this article are quite modest. For example, Bernstein et al. (2019) document a 4% discount for properties exposed to sea-level rise. For properties that might be affected within the next century, the authors find an even larger price effect of 7%. Baldauf et al. (2020) observe equally large discounts for sea-level rise exposure in "climate-believer" neighborhoods. Nationwide averages estimated by Hino and Burke (2021) are considerably smaller at a value of 2.1%. However, in states with the strictest flood risk disclosure, they estimate negative price effects of 4.1%. Although the observed discounts for sea-level rise are no larger than the extremes observed in our sample, they do exceed discount averages observed in our case. The difference in discount magnitudes is striking, as flood exposure in the Netherlands is already threatening properties today, rather than only 50 or 100 years from now. We interpret these relatively low exposure discounts as evidence that adaptation programs considerably mitigate economic value losses.

However, while adaptation mitigates exposure, it has its limits. Even in the best-protected areas, we observe significant flood risk discounts. This suggests that home buyers are not fully confident that the government can mitigate *all* risk or compensate them entirely for potential losses or nuisance from flooding. Moreover, there are pros and cons of implementing adaptation measures collectively. Collective adaptation measures have the benefit of being cost-effective, as single defenses protect multiple assets simultaneously. The downside is that the collective nature of such programs obstructs market mechanisms and invokes free-riding behavior. By enabling private owners to obtain the benefits of collectively paid adaptation measures (Bradt & Aldy, 2025), collective adaptation programs can stimulate people to sort into naturally exposed areas. This can incentivize further path-dependent development in sub-optimal places, causing even higher needs for future adaptation (Ouazad & Kahn, 2025). The collective Dutch approach thus raises a solidarity issue. Local taxes, such as those raised by water boards, might partly mitigate free-riding behavior if they link individual contributions to flood risk exposure.

Our results yield important implications for other geographies prone to flood risk—specifically, river deltas. Although these are challenging geographies, policy-makers can considerably limit negative price effects from flood risk exposure. Active adaptation programs, combined with proper institutions, can provide opportunities even to those places that appear to be most affected by climate change.

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APPENDIX

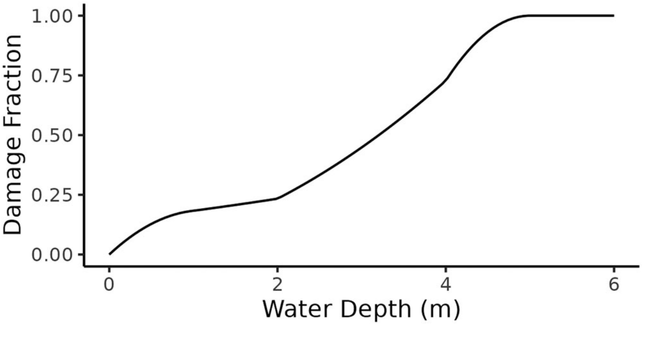

FIGURE A1 Damage function. *Note*: This figure presents the damage function for direct building and contents damage to single-family homes and is recreated from Slager and Wagenaar (2017).

TABLE A1 Summary statistics—continued.

Characteristic	Unembanked		Primary		Secondary		Regional	
	Unxposed $N = 35{,}737$	Exposed $N = 7{,}890$	Unxposed $N = 185{,}328$	Exposed $N = 386{,}363$	Unexposed $N = 133{,}803$	Exposed $N = 79{,}766$	Unexposed $N = 44{,}639$	Exposed $N = 3{,}513$
Categorical—%								
Property type								
Semi-detached	27	29	19	18	20	15	23	32
Corner	17	14	19	20	19	21	18	14
Terraced	3.6	4.3	2.4	3.2	3.1	3.3	3.1	4.0
Row house	38	34	47	49	45	50	45	33
Detached	15	18	13	10	13	10	11	17
Construction								
<1906	8.9	11	10	3.9	6.4	1.2	3.3	1.5
1906–1930	15	10	21	8.1	13	6.5	16	4.4
1931–1944	6.6	7.0	14	5.8	7.5	5.3	14	4.7
1945–1959	11	9.2	7.3	5.2	7.0	5.9	11	15
1960–1970	13	8.3	9.6	12	15	15	16	13
1971–1980	15	16	11	18	16	20	20	18
1981–1990	12	16	8.8	17	15	21	9.2	15
1991–2000	11	13	9.9	20	13	15	5.6	25
2001–2010	5.8	7.4	6.4	8.7	5.9	8.3	3.9	2.4
2011–2020	1.5	1.7	1.5	1.9	1.7	2.0	0.8	0.9
2021–2030	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1

Note: This table extends Table 1, comparing relevant building characteristics within and across flood zones.

TABLE A2 Summary statistics—complete.

Characteristic	Unexposed $N = 941{,}713$ Unexposed	Unembanked $N = 9347$ Unembanked	Primary $N = 533{,}058$ Primary	Secondary $N = 92{,}284$ Secondary	Regional $N = 3518$ Regional	Mixed $N = 161{,}942$ Mixed
Numeric—mean (SD)						
Price (×1,000)	279 (160)	261 (126)	268 (136)	285 (161)	270 (143)	288 (155)
Days on market	138 (233)	168 (267)	135 (229)	123 (200)	158 (251)	118 (187)
Volume (m^3)	423 (143)	464 (173)	404 (127)	397 (116)	441 (141)	393 (122)
Parcel (m^2)	269 (180)	293 (201)	231 (157)	216 (144)	290 (174)	204 (137)
Construction year	1,963 (35)	1,960 (45)	1,973 (32)	1,975 (24)	1,972 (26)	1,973 (26)
Abs. elevation (m)	14 (20)	18 (14)	2 (4)	−1 (5)	16 (15)	−1 (2)
Relief (cm)	0.11 (0.13)	0.18 (0.23)	0.10 (0.10)	0.10 (0.10)	0.11 (0.15)	0.10 (0.09)
Inundation (m)	0.00 (0.00)	1.00 (0.76)	1.74 (1.04)	0.82 (0.72)	0.40 (0.36)	1.71 (1.12)
Flood prob. (‰)	0.00 (0.00)	12.76 (24.85)	2.89 (4.32)	0.74 (0.85)	9.55 (15.83)	2.45 (2.58)
Flood hazard (×1,000)	0.00 (0.00)	1.69 (3.92)	1.28 (2.65)	0.09 (0.13)	0.94 (1.78)	0.98 (1.31)
Categorical —%						
< 200 m						
River: <3 m	33	28	49	52	43	57
River: 3–6 m	17	13	34	42	11	49
River: 6–12 m	28	17	55	77	53	79
River: 12–50 m	15	12	27	35	40	33
River: 50–125 m	1.1	12	2.9	2.5	1.0	3.4
River: >125 m	0.5	13	0.7	0.3	0	0.3
Lake: <0.1 mln m^2	28	31	33	33	38	36
Lake: 0.1:1 mln m^2	2.7	2.7	4.6	6.4	2.1	4.7
Lake: 1:10 mln m^2	0.6	0.9	1.3	3.0	0.7	1.7
Lake: >10 mln m^2	0.3	0.5	0.1	0.3	0	<0.1
Harbor: <10k m^2	0.4	2.1	0.5	1.0	<0.1	0.5
Harbor: >10k m^2	1.0	11	1.0	0.5	0.9	0.7
sea	<0.1	<0.1	<0.1	0	0	<0.1

Note: This table presents summary statistics off the full data sample.

TABLE A3 General flood exposure price effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposed	−0.012***	−0.013***	−0.013***	−0.015***	−0.014***	−0.012***	−0.009***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Elevation		−0.002***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
		(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Exposed × elevation		0.005***	0.004***	0.004***	0.003***	0.004***	0.005***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.932	0.932	0.949	0.954	0.955	0.957	0.962
R^2 Adj.	0.922	0.922	0.931	0.936	0.937	0.938	0.940
Num.obs.	1,781,698	1,781,698	1,781,698	1,781,698	984,985	898,485	667,389
Hedonics	X	X	X	X	X	X	X
YrQtr × district	X	X	X	X	X	X	X
Water amenity			X	X	X	X	X
City amenity				X	X	X	X
BDA cut-off					<1,000 m	<500 m	<200 m
Exposure variation					District	District	District

Note: This table presents ordinary least squares estimates, where the dependent variable is Ln(Price). Exposed is a dummy variable that equals one for a property exposed to flood risk. Hedonics accounts for property-specific characteristics through property volume, parcel size, and property volume × parcel size control variables and property type × construction period × inside quality × outside quality × monument fixed effects. Elevation is an integer that measures local variation in elevation. YrQtr × District accounts for year quarter × district fixed effects. Water amenity accounts for water accessibility. Column 1 estimates exposure effects using our entire data sample and only controlling for hedonic characteristics and general district price developments. Column 2 introduces local elevation controls. In Column 3, we add water amenity fixed effects. Column 4 adds city amenity fixed effects. In Columns 5 to 7, we restrict our data following the border discontinuity analysis approach (taking 1,000, 500, and 200 m as cut-offs, respectively). Additionally, we drop all observations in districts with no variation in exposure classes. T-statistics based on standard errors clustered at the six-digit postal code level are presented below the coefficients. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.

TABLE A4 Heterogeneity in flood risk pricing by exposure.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ExpClass = low	−0.011***	−0.012***	−0.015***	−0.016***	−0.015***	−0.012***	−0.010***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ExpClass = medium	−0.012***	−0.013***	−0.011***	−0.014***	−0.013***	−0.011***	−0.008***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ExpClass = high	−0.020***	−0.021***	−0.020***	−0.020***	−0.016***	−0.015***	−0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
ExpClass = very high	−0.018***	−0.020***	−0.035***	−0.033***	−0.032***	−0.033***	−0.033**
	(0.005)	(0.005)	(0.007)	(0.007)	(0.008)	(0.008)	(0.011)
R^2	0.932	0.932	0.949	0.954	0.955	0.957	0.962
R^2 adj.	0.922	0.922	0.931	0.936	0.937	0.938	0.940
Num.obs.	1,781,698	1,781,698	1,781,698	1,781,698	984,985	898,485	667,389
Hedonics	X	X	X	X	X	X	X
YrQtr × district	X	X	X	X	X	X	X
Exposed × elevation		X	X	X	X	X	X
Water amenity			X	X	X	X	X
City amenity				X	X	X	X
BDA cut-off					<1,000 m	<500 m	<200 m
Exposure variation					District	District	District

Note: This table presents ordinary least squares estimates, where the dependent variable is Ln(Price). The variable of interest is exposure and consists of five categories: unexposed, low, medium, high, very high, with unexposed as a reference. The exposure classification is based on the flood damage hazard from Figure 2c and takes the following cut-offs: 0, 0.0001, 0.001, 0.01, and 0.1. *T*-statistics based on standard errors clustered at the six-digit postal code level are presented below the coefficients. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.

TABLE A5 Flood exposure liquidity effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposed	−0.029***	−0.023***	−0.015*	−0.014	−0.016	−0.016*	−0.012
	(0.005)	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)	(0.010)
Damage factor	2.846	2.880	0.846	2.689	3.702	4.647	3.849
	(1.764)	(1.754)	(3.568)	(4.119)	(4.408)	(4.672)	(5.808)
RelElev		0.018***	0.021***	0.021***	0.021***	0.022***	0.022***
		(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
Exposed × RelElev		0.003	−0.004	−0.003	−0.002	−0.002	−0.004
		(0.002)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)
R^2	0.351	0.351	0.450	0.460	0.472	0.487	0.533
R^2 adj.	0.252	0.252	0.254	0.254	0.256	0.258	0.257
Num.obs.	1,781,698	1,781,698	1,781,698	1,781,698	984,985	898,485	667,389
Hedonics	X	X	X	X	X	X	X
YrQtr × district	X	X	X	X	X	X	X
Water amenity			X	X	X	X	X
City amenity				X	X	X	X
BDA cut-off					<1,000 m	<500 m	<200 m
Exposure variation					District	District	District

Note: This table presents ordinary least squares estimates, where the dependent variable is Ln(*Days of listing*). The table structure corresponds exactly to Table 3 in the article. *T*-statistics based on standard errors clustered at the six-digit postal code level are presented below the coefficients. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.

TABLE A6 Spatial autocorrelation robustness.

	(1)	(2)	(3)
Exposed	−0.009***	−0.009***	−0.009***
	(0.002)	(0.001)	(0.002)
Damage factor	−2.185**	−2.185**	−2.185*
	(0.812)	(0.673)	(1.089)
RelElev	−0.003***	−0.003***	−0.003**
	(0.001)	(0.001)	(0.001)
Exposed × RelElev	0.005***	0.005***	0.005**
	(0.001)	(0.001)	(0.001)
R^2	0.962	0.962	0.962
R^2 adj.	0.940	0.940	0.940
Num.obs.	667,389	667,389	667,389
Hedonics	X	X	X
YrQtr × district	X	X	X
Water amenity	X	X	X
City amenity	X	X	X
BDA cut-off	<200 m	<200 m	<200 m
Exposure variation	District	District	District
Cluster	PC6	Grid cell	PC5

Note: This table presents OLS estimates, where the dependent variable is Ln(*Price*). Column 1 corresponds to Table 2 and serves as a reference. Column 2 clusters the standard error at the damage hazard grid cell level, and Column 3 uses PC5 clusters. *T*-statistics are presented below the coefficients. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.