Dutch Dilemma: Housing Prices and Flood Risk Exposure

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Abstract

This paper studies the impact of forward-looking flood risk on the housing market in a major river delta. Analyzing 1.6 million property transactions from 1998 to 2023 in the Netherlands, we find an average price discount of 1.3% from the exposure to flood risk, with considerable heterogeneity in the average effect. We observe stronger discounts (up to 10%) in highly exposed areas, and discounts grow over time as climate threats become more imminent and awareness increases. The observed discount patterns suggest that homeowners make informed decisions. Nevertheless, price effects in most areas are modest compared to the possible impact of flooding events. We interpret these effects as market confidence in adaptability.

Acknowledgments

We are grateful to Brainbay and Deltares for providing us with data and to the NWA Red&Blue consortium for financial support. We thank Hans de Moel, Cees Oerlemans, Matthijs Kok, Ellen van Bueren, and Tom Daamen for providing us with the context of Dutch water management policies and practices. Moreover, we thank Franz Fuerst, Florian Grosset-Touba, Juan Palacios, Dongxiao Niu, Jaap Bos, and Zac Taylor for their valuable discussions, comments, and suggestions. We thank participants at the AREUEA International in Curacao, the Red&Blue Annual Symposium in Utrecht, and the UEA in Berlin for their suggestions. Lastly, we are grateful to Brainbay, Kadaster, the Dutch Association of Insurers, ING, ABN-AMRO, and the Climate Finance Academy for connecting us with industry professionals and for providing us with valuable feedback. Particularly, we want to thank Bas Boelhouwers, Lianne Hans, Vilon Ooms, Sophie Kraaijeveld, Mirjam Bani, Marc Brouwers, and Thijs Endendijk. All errors are our own.

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1 Introduction

Climate change increases both the frequency and intensity of extreme environmental events (Calvin et al. 2023) 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 (Krueger, Sautner, and Starks 2020; Zhang et al. 2018; Huang et al. 2022; Ouazad and Kahn 2022; Holtermans, Kahn, and Kok 2024). 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 coast lines or rivers, e.g. New York, London, Shanghai, Rotterdam, etc.

For households, real estate climate risk might play an even more significant role. Owner-occupied homes are the main source of household wealth in most OECD countries and roughly represent 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, Quigley, and Shiller 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).

A difficulty in the pricing of physical climate risk is the large amount of uncertainty surrounding these risks. While we know that climate change adds to these risks, exact impacts — specifically at the local level — remain unclear, due to the (in)adequacy of climate risk models and their parameters. In addition to scientific modeling uncertainty, future emission pathways remain unclear, as is the extent to which society can adapt to an altering climate (Millner, Dietz, and Heal 2013). Moreover, there is considerable heterogeneity in climate awareness and risk perception (Lee et al. 2015).

The joint effect of climate uncertainty, awareness, and risk perception causes markets to respond to climate risks in heterogeneous ways. A growing body of literature links market reactions to local beliefs. Such studies generally find that well-informed markets believing in climate change place discounts on real assets associated with climate risk (Yi and Choi 2020; Keys and Mulder 2020; Thompson et al. 2023;

Mase, Gramig, and Prokopy 2017; Gibson and Mullins 2020; Bakkensen and Barrage 2022; Beck and Lin 2020). In contrast, changes are much less pronounced in those markets where agents are skeptical about climate change or unaware of the risk (Bernstein, Gustafson, and Lewis 2019; Baldauf, Garlappi, and Yannelis 2020; Hino and Burke 2021; Fairweather et al. 2024). 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*, e.g. hurricanes, wildfires, etc. (Gibson and Mullins 2020; Ortega and Taşpınar 2018; Addoum et al. 2023; Garbarino and Guin 2021; Sutter and Poitras 2010; Götz, Mager, and Zietz 2024; Issler et al. 2024; Niu, Eichholtz, and Kok 2023). 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 either require frequent information updates that signal risk, or that risk tends to be overestimated directly after a climate shock.

While the literature documents clear evidence for heterogeneous outcomes in climate change risk pricing, it mainly focuses on the US — with a particular emphasis on Florida. This bias is understandable, given the data quality, the extent of climate shocks, and the variability in forward-looking climate risk. However, most findings cannot be generalized to other geographies, because outcomes depend strongly on local market characteristics — both in terms of geography and topography and in terms of institutions, such as insurance and lending markets.

To deepen the understanding of asset market responses toward physical climate risk, this paper focuses on the impact of climate risk — specifically river flood risk — on housing markets in 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 and 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, Stive, and Van Gelder 2009). These threats are not isolated but compound each other — e.g. 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 (Zscheischler et al. 2018; Qiu et al. 2022). In addition to being subject to significant and unique flood threats, deltas also 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.

While there are many important river deltas (e.g. the Pearl River Delta in China, the Mekong Delta in Vietnam, and the Ganges-Brahmaputra Delta in Bangladesh and India), we consider the Netherlands

— the combined delta of the Rhine, Meuse, Ems and Scheldt rivers — as an empirical test case. The Netherlands provides an interesting setting as it is highly exposed to several flood threats typical to a river delta. The consequences of climate change might be particularly dire, considering that almost half of the country lies below sea level (hence, the "Nether Lands", or low lands). At the same time, the Netherlands is a developed country that is well known for its expertise in water management. Hence it should be well-positioned to adapt to both present and future flood threats. By examining a setting where exposure is high, but where institutions and capital to adapt are also available, we can draw lessons on exposure pricing and market confidence in climate adaptability.

We exploit variation in flood exposure — both in space and over time — to assess the impact of flood risk on the housing market, using a sample of about 1.6 million transactions over the 1998-2023 period. The Netherlands has various levels of flood risk exposure and protection systems. To examine 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.

The findings in this study show strong 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 factors like buyer sophistication and availability of compensation policies. In addition to capitalizing *present* flood risk exposure, home buyers also seem to price *future* uncertainty — we observe a trend in which flood risk discounts are increasing, suggesting that homeowners indeed price the elevated risk from climate change. In addition, price effects seem dominant in areas where exposure is most obvious, such as unembanked areas and zones protected by primary dike systems. In line with the literature, we observe that sophisticated buyers demand larger price discounts as compared to less sophisticated buyers. Despite persisting differences, the less sophisticated segment also started to price flood risk in recent years. This "catching up" effect suggests an overall increase in flood risk awareness.

This paper adds to a rapidly developing stream of literature focusing on the pricing of physical climate risk. We highlight three related studies that also consider river delta flood risk. The works of Bosker et al. (2019), Mutlu, Roy, and Filatova (2023), and Daniel, Florax, and Rietveld (2009) focus on flood risk pricing in a similar setting. However, our study differs in four important aspects. First, we clearly distinguish between different types of flood zones and their associated risk — allowing us to explore market heterogeneity in more detail. Specifically, we consider price effects for exposure to storm surges,

dike failure, and river overflow, showing that price effects occur predominantly in unembanked flood zones and embanked areas with long-term inundation risk.

Second, we measure exposure through annual expected damage rather than examining maximum inundation and flood probability separately. This integrated approach allows for accurate risk assessment of many individual, but highly correlated, flood scenarios and aligns more with insurance industry standards on flood risk assessment.

Third, our identification strategy enables us to precisely distinguish between control and treatment groups at property-specific levels[1]. Using individual-level house price data not only provides detailed price effect estimates and a narrower definition of treatment and control groups, but it also enables us to account for property-specific elevation structures. Local elevation structures affect flood exposure but are not consistently captured by flood zone maps.

Last, the three studies claim that their outcomes are relevant in the light of climate change. However, none of the studies distinguishes between already existing risks and 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 findings in this paper have implications for policy makers that are tasked with the challenge of 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 seems to be successful in keeping exposed areas attractive, which can be especially useful in densely populated river deltas where space is scarce. Simultaneously, collective adaptation yields the risk of increasing exposure rather than reducing it, as both individuals and institutions have little incentive to avoid risk-prone areas.

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

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

2 Institutional Setting

2.1 Flood risk in the Netherlands

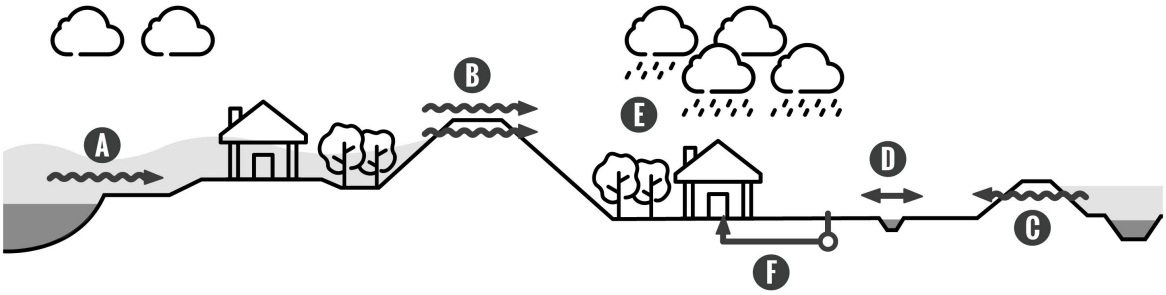
The Dutch coastal delta is a densely populated country prone to multiple flood threats. The country borders the North Sea in the North and West. Many places in these parts of the country are located below sea level. Because of this low elevation, many properties and households in the North and West face a direct threat of coastal flooding. Inland, two major river systems induce fluvial 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 (Moel, Aerts, and Koomen 2011).

Because of its geography, the Netherlands has one of the world's leading flood defense systems. The nation has established over 3,700 kilometers of water barriers. In addition to natural barriers such as dunes, there are approximately 1,500 constructed barriers, including dikes, dams, weirs, pumping stations, and storm surge barriers. These barriers are categorized into primary water barriers, which protect against external waters from the North Sea, Wadden Sea, major rivers and lakes, and secondary water barriers, which defend against internal waters from numerous lakes, smaller rivers, and canals (Bosker et al. 2019).

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-elevated coastal areas might, for example, enjoy protection from a primary dike to defend against inundation from the sea, while a secondary dike protects 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.

Figure 1: Causes of water nuisance and flooding in the Netherlands.



Notes: 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 and Deltares (2018).

The Dutch government is responsible for maintaining the country's flood defenses. It does so at multiple government levels. The national government (Ministry of Infrastructure and Water Management) is responsible for the primary dike systems that protect against flooding from the sea and main water bodies. More locally, water boards are responsible for regional defense systems. The primary flood protection measures are funded collectively, meaning that no differentiation in the amount of contribution is made based on personal exposure (Kaufmann, Priest, and Leroy 2018). The waterboards levy their own taxes, charged at the regional level, to operate. This allows them to work independently from national politics. Since waterboards set their own tax rates — enough to make all required investments — differentiation in terms of contribution by exposure happens at the regional level.

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, compensations have been made in earlier events, potentially affecting expectations. Additionally, the law states that costs are only eligible for compensation if they are not reasonably insurable.

It is important to note that home insurance policies distinguish between flood types. Floods in unembanked areas or floods that happen due to the failure of primary defense systems are non-insurable. This leaves relocation or private adaptation as the only option to avoid flood damage in these areas

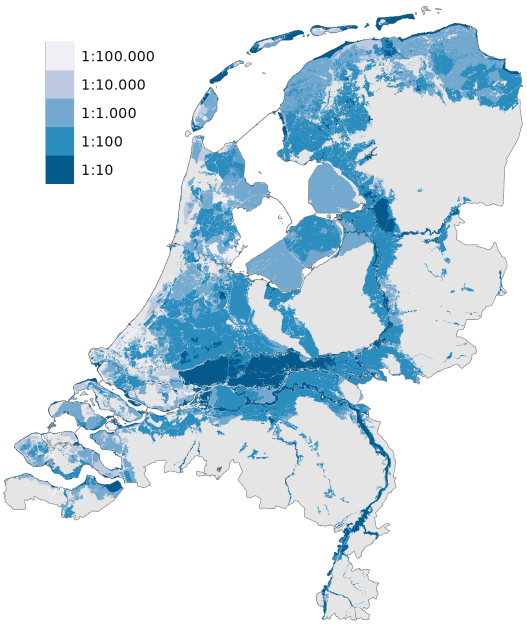
(Bosker et al. 2019). Damage as a consequence of regional flooding is covered by most insurers as part of the property insurance (Botzen and Van Den Bergh 2008). Whether and how insurers differentiate their fees based on forward-looking risk is important, as it affects price effect expectations. Unfortunately, such data is not publicly available.

Figure 2 presents flood maps of the Netherlands. Specifically, they show aggregated results of individual flood simulations based on various weather or flood defense failure scenarios. These flood simulations are tailored to specific scenarios and use advanced hydrological models[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). It should be noted that these flood hazards are calculated with individual scenario inputs rather than the aggregated results from Figures 2a and 2b, as different maximum inundations can occur at various flood probabilities. Since Figure 2c effectively combines exceedance probabilities and inundation into a single denominator, this is also the measure that we use in our empirical analysis.

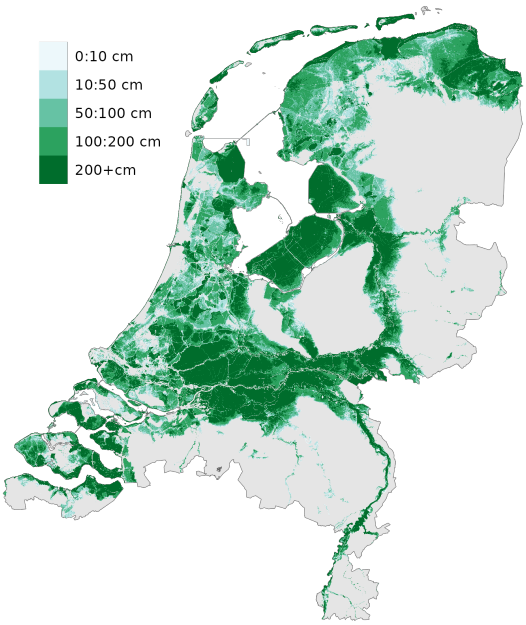
The spatial distribution of the different types of flood zones is shown in Figure 2d. The unembanked areas (corresponding with Figure 1 type A) are located along the coast, large lakes, and big rivers and are affected by coastal and fluvial flooding. Because these areas are not protected, flood probabilities tend to be high. On the other hand, maximum inundation is limited as water can easily escape. 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 dikes (corresponding with Figure 1 type B). Because these dikes have the highest level of safety standards, the probability of failure is extremely small. At the same time, inundation can be quite substantial, as elevation levels behind the dikes are typically low. As such, we can still observe very high risk within this type of flood zone. An additional characteristic is that water needs to be pumped out once a primary dike fails. Hence, it could take months before areas become livable again after a dike failure. Secondary dikes (corresponding with Figure 1 type C) are similar to primary dikes but protect against smaller water bodies. Because of this, areas protected by secondary dikes tend to have less exposure, despite lower than primary dike safety standards. Regional defense systems (corresponding with Figure 1 type D) are primarily located in the

2. These models use several inputs — like precipitation, soil types, elevation, and dike breaches — to estimate maximum inundations. The likelihood that a specific scenario occurs is then associated with a flood depth (Leandro et al. 2009). The aggregation of these individual scenarios provides an overview of the flood risk the country is facing as of 2020 — although the aggregated flood maps present exposure as of 2020, individual flood scenarios can be based on older data inputs. Examples of hydrological models used for the flood simulations are Sobek and the GlobalFLoodRiskTool from water engineering companies Deltares and RoyalHasKoningDHV respectively.

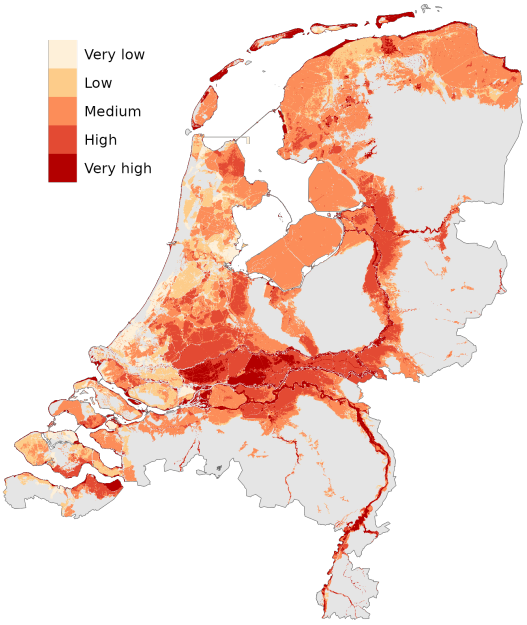
Figure 2: Dutch 2020 flood maps



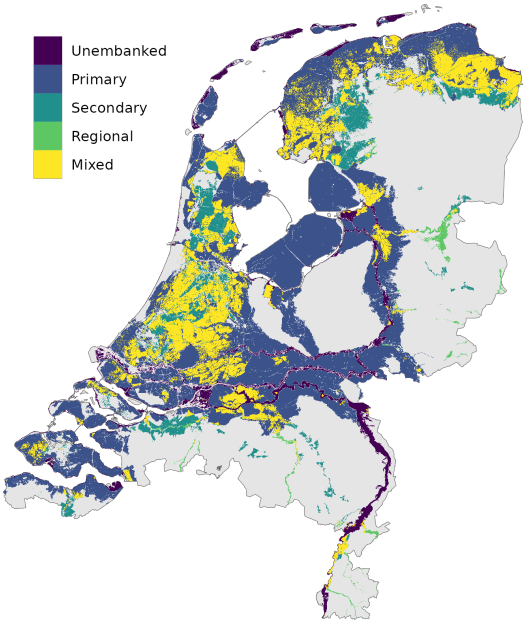
(a) Annual Exceedance Probability



(b) Maximum Inundation



(c) Flood Damage Hazard



(d) Flood Zones

Notes: 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 (Figure 2a); the most extreme inundation (Figure 2b); and the sum of individual single-family house damage functions (see Figure 4) multiplied by the probability that a specific scenario will occur (Figure 2c). See De Bruijn et al. (2015) for details. The input data for Figures 2a to 2c 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 Figure 2d is created using the maximum inundation flood zones per protection system. This data is publicly available at www.basisinformatie-overstromingen.nl

higher altitude parts of the country, in the East and South. While inundation tends to be low for these exposure zones, flood probabilities are rather high. The mixed flood zones indicate areas where different flood exposures overlap. The majority of overlap occurs between primary and secondary flood zones.

For interpretation, it is important to note that these maps are developed for water engineering purposes. Therefore modeling decisions tend to be on the safe side. 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 underestimate future risk. Given this range of uncertainty, we do not attach much value to exact probabilities and flood hazard values. Rather, we merely distinguish between the extent of risk by classifying "very low" to "very high" exposure zones.

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 inundation maps do not merely indicate current risk but also signal historic and future threats.

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.

2.2 Individual Adaptation

The Dutch flood defense system acts as a collective adaptation measure towards flood risk. Nevertheless, people 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.

The flood maps in Figure 2 are rather granular, using 25 squared meter grid cells. Hence, they already account for most elevation changes at the local level. Nevertheless, considerable variety can occur within twenty-five meters. For flood events where maximum inundation is limited, such variations can be a driving factor in determining whether houses get flooded. To account for within-grid cell exposure variation we introduce two local elevation measures.

We control for relative elevation by measuring the absolute elevation of a 5-meter and 10-meter ring around each property. Subtracting the latter from the former indicates whether or not a property is elevated compared to its surroundings [3]. The relative elevation measure proves inadequate if a property is on a slope. Hence, we also control for relief by measuring the standard deviation of absolute elevation in 5-meter ring buffers around each property.

2.3 Risk Perception and Flood Risk Pricing

In normal circumstances, the Netherlands is well adapted to discharge rain and melt water and protect the coast from storm surges. Rivers are modified to effectively dispose of water, avoid silt ups, and are strengthened by an advanced system of dikes; numerous flood plains act as buffers to ensure safety at times of peak discharge; and the entire coast is protected by a system of dikes and dunes. During storm surges, estuaries can be closed off by water barriers, while various pumping stations allow for continuous water disposal and enable below-sea-level living (Ven 1993). Still, despite 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 and Zhang 2015). A recent example where defense measures proved inadequate is the 2021 flash flooding in the South of the Netherlands. These floods roughly 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)

In contrast to common belief, the most imminent flood threat for the Netherlands and other deltas is not coastal but comes from the rivers. The reason for this is that, in contrast to long-term sea-

3. The decision to use 5-meter 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 get reliable means.

level rise, weather patterns are already altering now. Climate change affects flood risk exposure both directly and indirectly. Directly, extreme precipitation and melting glaciers add to higher peak discharge, putting higher requirements on the water-bearing capacity of the river systems (Skougaard Kaspersen et al. 2017). Indirectly, more extreme water patterns add to dike and soil deterioration through the following processes: higher peak discharge adds to the probability of overtopping — a process where water skips over a dike, causing water to spill in the land behind and eroding the inner slopes; increasing winter precipitation can saturate the soils, so reducing dike stability and increasing its proneness to erosion and piping; drier summers add to dike deterioration's through soil shrinking and cracking; increasing drought can cause land subsidence and thus add to larger inundation (Wiel et al. 2024; Schmocker and Hager 2012; Oude Essink, Van Baaren, and De Louw 2010).

The impact of climate change has sparked a debate on acceptable risk levels, but the Netherlands has always been prone to flooding. Climate change only adds incremental risk to this flood exposure. Given that this incremental risk is added only gradually, it is hard to distinguish separate effects of ever-present and elevated risk due to climate change. For this purpose, one would ideally measure the effects of places that were not at risk ex-ante, but now become so due to climate change. A natural experiment with such an external climate shock did not occur in recent times. Hence, establishing a causal relation between climate change and flood risk proves to be difficult. Rather than establishing such a causal relation, we seek to answer a different question. First and foremost, we aim to investigate whether flood exposure is priced, and if so, to what extent. Second, by distinguishing between ever-present flood risk discounts and climate change-induced incremental discounts, we hope to give some indication to what extent home buyers consider climate change in their buying decisions.

3 Empirical model

To identify the capitalization of flood-related risk, we employ an empirical design comparing the transaction prices of houses with varying flood risk exposure to unexposed houses. 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, D'Oria, and Rizzo 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[4]. Moreover, we omit observations that are in both exposed and non-exposed grid cells, to limit the risk of false positives and negatives.

Proximity to water adds risk but also comes with amenities (Mutlu, Roy, and Filatova 2023; Bonetti et al. 2016; Jauregui, Allen, and Weeks 2019; Simons and Saginor 2006). We account for the "water amenity" by including water amenity fixed effects. In line with Bernstein, Gustafson, and Lewis (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. Those 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 3m, 6m 12m, 50m, and 125m 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 taking 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 areas as the cut-off. Smaller harbors tend to be used for recreational purposes while larger harbors — like the port of Rotterdam — can 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, e.g. 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 relatively 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

4. An alternative would be to take 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.

cluster if they are connected to other restaurants within a 50-meter radius. We use distance to cluster bins of 0 to 1000 meters with 100-meter intervals.

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

$$ln(Price)_{it} = \beta_1 Exposed_i + \beta_2 Exposed_i * Elevation_i + \beta_3 Exposed_i * Relief_i + \beta_4 BuildingVolume_i + \beta_5 ParcelSize_i + \beta_6 BuildingVolume_i * ParcelSize_i + \gamma_i + \delta_{it} + \zeta_i + \epsilon_{pc6} \quad (1)$$

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; $Relief$ is a continuous measure of local relief; $BuildingVolume$ is a continuous measure of the properties 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; and ζ_i captures access to water amenities and historic city center amenity value.

Our variable of interest is the flood exposure coefficient (Exposed). Since the relation between flood hazards and log house prices is not necessarily linear we consider flood hazards in two ways. In our 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 six categories. We take the cut-offs at 0.00001, 0.0001, 0.001, 0.01, and 0.1 to create the following flood hazard categories: *very low hazard*, *low hazard*, *medium hazard*, *high hazard*, and *very high hazard*. Following the flood hazard definition, this means that properties with very low exposure can expect annual damage of less than 0.0001% of their building value. For properties with very high exposure, the expected annual damage is between 1% and 10% of the building value. Again, we consider properties with no flood hazard specification or a value of 0 as unexposed.

Exposure interacted with relative elevation (Exposed * Elevation) and exposure interacted with relief (Exposed * Relief) controls for highly local exposure variation unobserved in our flood exposure map. The interaction term allows us to distinguish general elevation and relief benefits from those specific to properties in flood zones. To account for any remaining location effects that might induce autocorrela-

tion, we cluster our error term using PC6 dummies – PC6 areas correspond to the smallest ZIP codes with on average 7 observations per zone.

4 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, Brounen, and Kok 2020; Van Ommeren, Wentink, and Dekkers 2011; Gaigné et al. 2022).

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 strengthens our belief that individuals can access this information[5].

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

5. 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.

development. The water bodies in this dataset are derived from areal pictures and are highly accurate (0.1 meter margin of error). In addition to providing the geographical scope of water bodies, several classifications are used to qualify these water bodies, e.g. the name of the water body, whether it is part of the main river system and river width[6]. 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.

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 (raster size of 0.5 by 0.5 meters) 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. We aggregate the raster size in this dataset to 1 by 1 meter.

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 three 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 (more than 2 mln euros) and low prices (less than 50,000 euros); 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. Last, we remove all observations with contradicting flood exposure values, to ensure clear treatments and controls. 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.

Summary statistics of the final dataset are presented in Section 4. We observe that the average prices of unexposed properties are higher than those of exposed properties when located in unembanked

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

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.

The absolute elevation is not different for exposed and unexposed homes in unembanked areas, but for the remaining zones unexposed properties tend to be located at lower elevations. Local property elevations tend to be similar. However, exposed properties in regional dike areas are slightly more elevated compared to their unexposed comparables. The maximum inundation is by far the highest in primary dike areas with an average of 1.68 meters. 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. 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 construction periods in which relatively many properties are built in unsafe areas. Especially the period 1981-1990 stands out here.

Table 1: Summary statistics

Characteristic	Unembanked		Primary		Secondary		Regional	
	Exposed N = 6,642	Unexposed N = 29,051	Exposed N = 378,338	Unexposed N = 157,676	Exposed N = 69,944	Unexposed N = 109,281	Exposed N = 3,058	Unexposed N = 37,280
Numeric — Mean (SD)								
Price (€ x1000)	237 (103)	252 (118)	249 (115)	270 (143)	256 (129)	249 (124)	242 (104)	242 (120)
Days on market	152 (239)	145 (232)	125 (211)	126 (222)	119 (196)	123 (210)	157 (254)	126 (210)
Volume (m3)	421 (138)	401 (128)	375 (101)	372 (116)	370 (90)	375 (107)	415 (112)	406 (117)
Parcel (m2)	250 (170)	224 (143)	190 (118)	194 (136)	191 (115)	203 (129)	266 (153)	218 (130)
Abs. elevation (m)	17 (14)	16 (16)	2 (4)	4 (7)	0 (6)	4 (8)	16 (16)	18 (22)
Rel. elevation (cm)	6 (12)	6 (12)	6 (7)	5 (9)	6 (7)	6 (7)	6 (8)	6 (8)
Relief (cm)	19 (24)	17 (24)	10 (10)	13 (17)	9 (9)	10 (12)	11 (15)	12 (15)
Inundation (m)	0.94 (0.78)	0.00 (0.00)	1.55 (1.02)	0.00 (0.00)	0.72 (0.70)	0.00 (0.00)	0.40 (0.36)	0.00 (0.00)
Flood prob. (‰)	13.06 (25.41)	0.00 (0.00)	2.44 (4.10)	0.00 (0.00)	0.72 (0.83)	0.00 (0.00)	10.11 (16.74)	0.00 (0.00)
Flood hazard (x1000)	1.67 (4.18)	0.00 (0.00)	1.06 (2.57)	0.00 (0.00)	0.09 (0.12)	0.00 (0.00)	1.01 (1.94)	0.00 (0.00)
Categorical — %								
< 200 meters = TRUE								
River: <6m	29	29	56	43	62	56	47	25
River: 6-50m	32	31	68	52	82	65	71	29
River: >50m	24	9.3	3.9	5.1	3.1	4.0	1.1	1.0
Lake: <1mln m^2	33	20	30	27	34	31	36	23
Lake: 1-10mln m^2	1.6	1.8	4.2	2.7	5.5	3.9	1.3	2.1
Lake: >10mln m^2	1.0	4.1	1.1	1.8	2.2	1.5	0.8	0.6
Harbor: <100k m^2	2.4	0.9	0.7	1.0	0.9	0.9	<0.1	0.6
Harbor: >100k m^2	12	7.0	1.5	3.8	0.4	1.1	0.8	0.8
Sea	<0.1	<0.1	<0.1	<0.1	0	<0.1	0	0

Summary statistics (cont.)

Characteristic	Unembanked		Primary		Secondary		Regional	
	Exposed N = 6,642	Unexposed N = 29,051	Exposed N = 378,338	Unexposed N = 157,676	Exposed N = 69,944	Unexposed N = 109,281	Exposed N = 3,058	Unexposed N = 37,280
Categorical — %								
Property type								
Corner	15	18	21	21	23	20	15	20
Detached	14	11	6.0	9.3	6.3	9.2	12	8.1
Row house	37	39	55	51	55	48	37	48
Semi-detached	30	28	15	17	13	20	33	22
Terraced house	3.9	3.3	2.3	1.9	2.4	2.4	2.9	2.4
Construction period								
<1906	9.3	7.7	4.0	9.1	1.3	6.0	1.1	2.7
1906-1930	10	15	9.1	21	6.7	12	4.2	15
1931-1944	7.5	6.4	6.4	13	4.3	6.4	3.2	13
1945-1959	9.5	11	5.6	8.2	6.0	7.3	15	11
1960-1970	8.1	15	12	10	16	16	13	18
1971-1980	16	16	19	12	20	17	18	21
1981-1990	18	13	17	9.3	25	16	16	9.5
1991-2000	13	10	17	9.2	12	12	26	4.7
2001-2010	6.8	5.0	7.4	6.1	7.1	5.5	2.3	3.6
2011-2020	1.7	1.3	1.6	1.6	1.7	1.9	0.9	0.8
2021-2030	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1

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.

5 Results

The results of our empirical analysis are presented in the following section. First, we examine whether flood exposure is priced in general. Second, we consider the impact of exposure intensity. Third, we consider price effects across different flood zones. Fourth, we look into temporal price effect variation. Last, we consider the impact of buyer sophistication.

5.1 Baseline Results

Table 2 presents the ordinary least squares estimates of the natural log of the transaction price on the independent variable, flood hazard, with "no exposure" as the reference category. 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, the presence of a flood hazard decreases the price of a property by 1.1% or 2,750 euros at the point of means. In column 2 we account for property-specific adaptation through relative elevation and relief measures. With a value of 1.8%, the exposure discount becomes considerably stronger, suggesting that there is indeed substantial variation in exposure that is not captured by the coarse flood exposure maps. In column 3 we rigorously account for water amenities. Controlling for water amenities increases the strength of the flood exposure coefficient to a level of 2.1%. This increase in strength suggests that the water amenity fixed effects indeed pick up some of the correlation between water premiums and flood exposure. 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 the model specification in columns 1 to 4 is quite strict, unobserved structural characteristics might still affect our results. Hence, we restrict our data even further in columns 5 to 7. Starting with column 5, we implement a border discontinuity approach as described by Bosker et al. (2019). This 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. As a first cut-off point, we use 1,000 meters, so that the data only contains properties less than one kilometer away from a flood border. This omits about a third of our observations. The large share of transactions in proximity to flood zones illustrates that most Dutch houses are clustered in areas close to water. The flood exposure coefficient remains 1.8%. We further tighten our model in column 6 by setting the border discontinuity cut-off point at 500 meters. This slightly reduces the strength of our coefficient of interest, to a value of 1.5%. Despite the slight decline in strength, the discount remains robust. Column 7 shows results for the tightest model specification. Here we only consider transactions no further than

Table 2: General flood exposure price effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposed	−0.011***	−0.018***	−0.021***	−0.021***	−0.018***	−0.015***	−0.013***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
R2	0.922	0.922	0.946	0.954	0.958	0.960	0.966
R2 Adj.	0.910	0.910	0.921	0.929	0.932	0.933	0.935
Num.Obs.	1 565 224	1 565 224	1 565 224	1 565 224	1 007 902	912 672	670 788
Hedonics	X	X	X	X	X	X	X
YrQtr x District	X	X	X	X	X	X	X
RelElev x ExpClass		X	X	X	X	X	X
Relief x ExpClass		X	X	X	X	X	X
Water Amenity			X	X	X	X	X
City Amenity				X	X	X	X
BDA cut-off					<1,000m	<500m	<200m
Exposure variation					District	District	District

Notes: 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 x parcel size control variables and property type x construction period x inside quality x outside quality x monument fixed effects. RelElev x ExpClass is an integer of relative elevation interacted with the flood exposure class. Relief x ExpClass is an integer that measures variation in elevation surrounding a property interacted with the flood exposure class. YrQtr x District accounts for year quarter x 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 and relief 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 meters 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.

200 meters from a flood border. We observe a slight reduction in strength with a discount of 1.3%, but the discount remains both statistically and economically (3,315 euros at the point of means) significant[7].

5.2 Heterogeneous Effects

5.2.1 Flood Hazard Factor

In Table 3 we split the flood hazard into individual buckets. Equal to the baseline results we progressively add controls in columns 1 to 4 and restrict our dataset in columns 5 to 7.

In the loosest model specification, discounts range from 1.1% to 2.4% or €2,780 to €6,070 at the point of means. From the low to very high exposure categories the discounts follow a logical pattern in which more exposure equals higher discounts. The coefficient pattern does not hold entirely but remains logical once considering

7. The weakening of the effect in columns 5, 6, and 7 might be explained by a reduction in actual exposure rather than omitted structural characteristics. The average damage hazard factor for exposed properties declines along with the observed discount rate from 0.000982 for the entire data (columns 1 to 4) set to 0.000804 in the tightest model specification (column 7).

Table 3: Heterogeneity in flood risk pricing by exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure = very low	−0.011***	−0.016***	−0.017***	−0.017***	−0.014***	−0.010**	−0.010**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Exposure = low	−0.009***	−0.018***	−0.019***	−0.018***	−0.015***	−0.011***	−0.010***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Exposure = medium	−0.009***	−0.016***	−0.017***	−0.018***	−0.015***	−0.014***	−0.012***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Exposure = high	−0.020***	−0.029***	−0.023***	−0.025***	−0.020***	−0.019***	−0.017***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Exposure = very high	−0.024***	−0.053***	−0.062***	−0.066***	−0.064***	−0.071***	−0.096***
	(0.006)	(0.007)	(0.010)	(0.012)	(0.012)	(0.013)	(0.019)
R2	0.922	0.922	0.941	0.950	0.955	0.957	0.962
R2 Adj.	0.910	0.910	0.918	0.926	0.929	0.930	0.933
Num.Obs.	1 565 224	1 565 224	1 565 224	1 565 224	1 007 902	912 672	670 788
Hedonics	X	X	X	X	X	X	X
YrQtr x District	X	X	X	X	X	X	X
RelElev x ExpClass		X	X	X	X	X	X
Relief x ExpClass		X	X	X	X	X	X
Water Amentity			X	X	X	X	X
City Amenity				X	X	X	X
BDA cut-off					<1,000m	<500m	<200m
Exposure variation					District	District	District

Notes: this table, presents ordinary least squares estimates, where the dependent variable is Ln(Price). The variable of interest is exposure and consists of six categories: unexposed, very low, 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, 0.00001, 0.0001, 0.001, 0.01, and 0.1. The table follows an identical structure to Table 2. However, because water distance buckets can pick up exposure rather than accessibility, we slightly relax our fixed effects specifications in columns 3 to 7. Rather than interacting water distance combinations with districts we use municipalities instead. 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.

confidence intervals, e.g. the -0.011 very low exposure coefficient is not significantly different from the -0.009 low exposure coefficient. Introducing the two local elevation measures strengthens the discount magnitudes across the exposure risk distribution. The overall pattern, where higher exposure is associated with larger discounts, persists. The introduction of water amenities in column 3 increases the significance of all coefficients. The largest change in discount occurs in the very high exposure category, where discount rates increase from 5.3% to 6.2%. The particularly large effect in this exposure category makes sense intuitively, as it also contains the properties with the best access to large water bodies. Introducing the access to city amenity measure in column 4 only slightly changes the coefficients.

Restricting the observations in column 5 slightly weakens the magnitude of the coefficients along the risk distribution. Despite the drop in magnitude, discounts remain significant across the distribution and the increasing exposure/discount pattern persists. Column 6 restricts our data even further. Again,

we observe an overall drop in magnitude, except for the very high exposure class — a likely explanation is that we missed some water amenity values for this exposure class. In our tightest model specification, we again observe slightly smaller discount magnitudes in the four lowest exposure classes and a further strengthening of the highest exposure class. Despite the tight model specification discounts remain highly robust and both statistically and economically significant at rates ranging from 1.0% up to 9.6% or €2,580 and €25,540 at the points of means.

5.2.2 Flood Types

Our results so far highlight general discounts across all flood types. However, unobservable variations in exposure can cause outcomes to differ per flood type. Our exposure measure captures damage hazards as a function of flood probability and maximum inundation. Other factors contributing to risk — such as flood duration and flow speed — remain unconsidered. Since specific defense systems protect against specific water bodies, accounting for the type of defense through flood zones should capture most of this unobserved variation. In addition, the type of flood zone has important institutional implications. Flood zones differ in terms of who is liable, whether or not homeowners can expect compensation in a disaster event, and whether insurance coverage is available, or not.

We consider unembanked areas, flood zones protected by primary dikes, flood zones protected by secondary dikes, regional flood zones, and mixed flood zones (as in Figure 2d). Besides differences in physical exposure, each flood type is subject to different institutional policies. Unembanked areas enjoy the least security. Owners cannot insure their houses against flooding in these areas, nor are they entitled to compensation from the Calamities and Compensation Act. In primary dike zones, there is in case of a flood no provision for flood insurance either, but here homeowners are entitled to (partial) compensation. In regional flood areas insurance is possible, and because of that, owners are not entitled to flood disaster compensation in case of flooding.

To estimate the effect of flood exposure per flood type, we replace the exposure variable with flood zone classes in which a property is located. We only consider the combination of primary dike with secondary dike since other combinations yield only a few observations. For that reason, we have slightly fewer observations than in the other regression tables. Again, we consider no exposure as the reference category.

Across all model specifications, discounts seem to be driven by unembanked areas, primary dike areas, and mixed primary and secondary zones. The significance and strength of the discounts in primary dike

Table 4: Heterogeneity by flood zone

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ExpType = unembanked	−0.001	−0.012*	−0.037***	−0.042***	−0.041***	−0.038***	−0.047***
	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)	(0.009)
ExpType = primary	−0.014***	−0.022***	−0.027***	−0.026***	−0.022***	−0.020***	−0.017***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
ExpType = secondary	−0.005**	−0.013***	−0.004	−0.003	0.000	0.001	0.000
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
ExpType = regional	0.027***	0.020***	0.009	−0.002	0.002	0.000	−0.001
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
ExpType = mixed	−0.017***	−0.024***	−0.022***	−0.026***	−0.022***	−0.020***	−0.018***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
R2	0.922	0.922	0.946	0.954	0.958	0.960	0.966
R2 Adj.	0.910	0.910	0.921	0.929	0.932	0.933	0.935
Num.Obs.	1 564 251	1 564 251	1 564 251	1 564 251	1 006 929	911 699	669 844
Hedonics	X	X	X	X	X	X	X
YrQtr x District	X	X	X	X	X	X	X
RelElev x ExpClass		X	X	X	X	X	X
Relief x ExpClass		X	X	X	X	X	X
Water Amentity			X	X	X	X	X
City Centre				X	X	X	X
BDA cut-off					<1,000m	<500m	<200m
Exposure variation					District	District	District

Notes: 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. Column 1 indicates total effects and serves as reference. Column 2 restricts the data to unexposed properties and those in unembanked areas. Column 3 restricts the data to unexposed properties and those in primary dike flood zones. Column 4 restricts the data to unexposed properties and those proptected by regional defense systems or exposed to regional surface water. 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. [a] Due to limited observations we do not interact volume and parcel percentiles with the other hedonic characteristics in the fixed effects specification. Alternatively, we account for hedonic characteristics using volume percentiles x parcel percentiles fixed effects and dwelling type x construction period x interior quality x exterior quality x monument status fixed effects.

areas are noteworthy as the government is liable for ensuring safety in primary dike areas and will likely compensate homeowners in the event of a disaster. The fact that we still observe a considerable discount indicates that people are either not aware of their entitlement to compensation, or it reflects the belief that this compensation will be insufficient. It is indeed unlikely that the disaster compensation offsets all costs, as it involves a partial compensation that accounts for direct physical damage. This neglects indirect costs like (financial) hardship, location devaluation, health risk, and costs due to temporal reallocation. In this regard, it is important to note that — in contrast to unembanked areas — primary dike breaches lead to long-lasting inundation. In these zones, flood water does not run off by itself and needs to be pumped out. Hence, it can take months before areas become inhabitable again after such a disaster. Besides limited coverage, disaster compensations are also prone to political decisions.

An event should be declared a disaster before any compensation will be made. Moreover, there is no guarantee that properties will remain covered by disaster compensation in the future. Finally, primary dike breaches are high-impact, low-probability events. The relatively large discounts for a given level of hazard exposure align with evidence that risk preferences depend non-linearly on outcome probabilities (Fehr-Duda and Epper 2012).

The lack of flood exposure pricing in regional and secondary dike areas is remarkable as it involves a type of flood risk that can be privately insured and is not covered by the Calamities and Compensation Act. One would expect that insurance fees clearly signal the costs of flood exposure. A possible explanation for the absence of a discount is that flood exposure tends to be smaller in regional dike areas than in primary dike or unembanked areas. It could thus be that this exposure is considered small enough for people to neglect it.

Additionally, we consider flood duration and the insurance setting as likely explanations. In contrast to the long-lasting impacts of primary dike breaches, regional flood events are short-lived. Considering the indirect costs of long-term inundation, homeowners might indeed require less compensation for similar exposure in regional flood zones and secondary dike areas compared to primary dike areas. Regarding insurance, it is important to note that flood insurance is not a stand-alone product, but tends to be part of an overall home and content insurance bundle. The fact that insurance fees entail multiple types of risk can mask individual pricing signals. Moreover, it is unclear to what extent insurers differentiate their fees. If insurance fees do not clearly distinguish between individual exposure, they can incentivize risky behavior. For example, people might prefer risky areas with water amenities if they get full insurance without paying extra. For this to be true, not all insurers need to provide homogeneous insurance fees, as homeowners can easily compare fees at dedicated websites and pick the one that covers flood risk at the lowest costs.

5.2.3 Temporal Effects

The previous analyses considered price effects from flood risk as fixed. However, this assumption may well be invalid in the context of climate risk. Given the incremental risk caused by climate change, we expect effects to increase over time. At the same time, there have been ongoing efforts to mitigate flood risk in the Netherlands. Although these adaptation programs do not fundamentally change exposure zones, they may alter the observed price effects per exposure class. Specifically, we observe exposure per 2020 while transactions go back to 1998. Mitigation projects that took place between the property

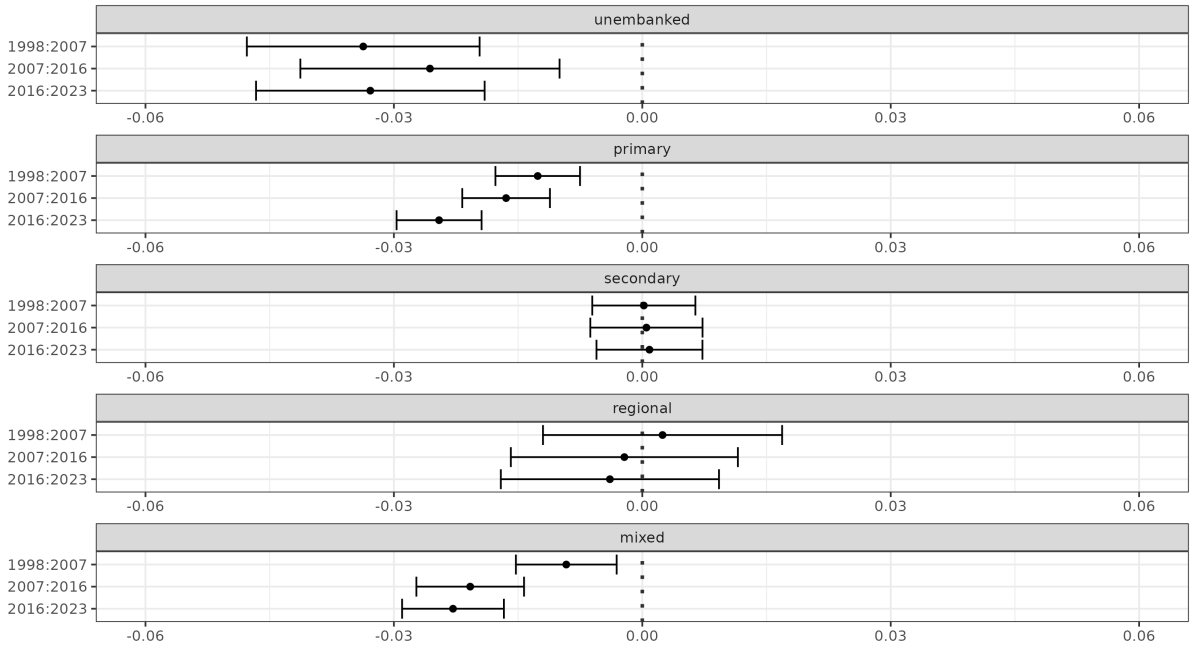
transaction date and the time when the flood simulation — relevant for that property — was performed, can cause an underestimation of exposure at the time of sale.

To identify temporal variation, we adapt our variable of interest into an exposure class by transaction period interaction. To ensure enough observations in all exposure classes and transaction periods, we specify the periods by transaction date tertiles. We take the 500 meters as the border discontinuity cut-off. Moreover, we interact water amenity distance buckets with COROP areas — a regional classification system between the municipality and province — rather than districts for the fixed effects specification to ensure enough statistical power. The model specification equals Column 6 of the main model (Table 2), except for the independent variable alteration and the water amenity fixed effects.

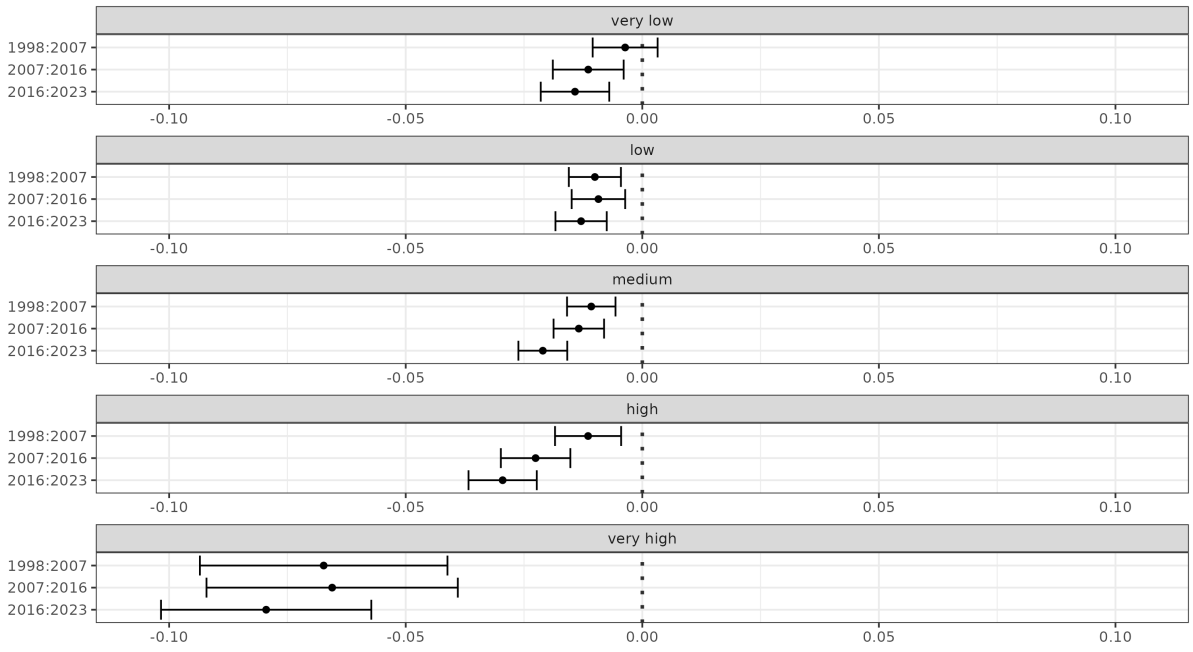
The coefficients for the exposure and transaction periods are plotted in Figure 3b. Panels present different exposure classes, the y-axes indicate transaction periods, and the x-axes show price effects. Considering the average discount per exposure class, we observe a pattern that matches the results from Table 3. Observing discounts per individual period, we see an interesting trend where discounts seem to increase over time. For example, in the "very low" exposure category we observe no significant price effect in the 1998:2007 period, but the discount becomes significant in the 2007:2016 and appears to grow further in the 2016:2023 period. In the higher exposure categories discounts are already significant in 1998:2007. However, also here we can observe an increase in the magnitude of the effect in the consequent periods with significant differences for the medium and high exposure categories. We acknowledge that not all of these time effects are significantly different from one another. However, we interpret the pattern that is roughly increasing across all exposure classes as evidence for a growing discount trend. The increasing discount trend aligns with assumptions on larger exposure due to climate change and matches with findings in related flood exposure studies (e.g. Bernstein, Gustafson, and Lewis 2019).

Some notable deviations from the overall growing discount pattern can be observed. For the unembanked flood zones and the "low" and "very high" exposure categories price effects seem to weaken rather than strengthen in the 2007:2016 period. We posit three explanations for these deviations. First, 2007-2016 largely overlaps with a period of stagnating house prices that followed the 2008 financial crisis. Changes in market dynamics might have affected required discounts. However, below-trend discounts in the bottom four exposure classes seem counterintuitive here. One would expect more risk aversion — and thus larger discounts — in times of financial distress. Second, 2005 marked the start of a flood risk mitigation program, in which important objectives were achieved in 2015, 2017, and 2019. This program

Figure 3: Time Variation in Flood Risk Pricing



(a) Time by type



(b) Time by exposure

Note: This figure presents Ordinary Least Squares estimates, with Ln(price) as the dependent variable and Exposed = TRUE × Transaction Period as the key independent variable. Transaction periods are defined as sale date quintiles. Controls include property characteristics; year-quarter × district fixed effects; water amenities; relative elevation; and relative elevation x exposure = TRUE, consistent with the main model (Table 2). The sample is restricted to properties within 500 meters of a flood zone border, excluding districts lacking flood exposure variation. T-statistics based on standard errors that are clustered at the six-digit postal code level are presented as 5% significance confidence intervals.

might first have signaled and then reduced exposure in the relevant flood zones. Last, the Disaster Damage Relief Act has been used for compensation a total of six times — twice in 1998, twice in 2003, once in 2011, and once in 2021. Such compensation could have signaled that financial damages are covered by the wider market and thus suppress observed discounts. An opposite effect might have been achieved in 2016 when the government chose not to compensate for flood damage after an event, potentially setting a precedent.

5.2.4 Buyer Sophistication

In addition to understanding how flood risk capitalization developed over time, we are interested in heterogeneity across market segments. In a key study, Bernstein, Gustafson, and Lewis (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 the price range of the property. Buying in the top market segment of the housing market 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. We classify market segments by ranking transaction prices per transaction year and district. The 50% of transactions with the lowest (highest) prices are marked as the bottom (top) segment.

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, Gustafson, and Lewis (2019), listed properties in the Netherlands tend to receive multiple bids. If unsophisticated buyers consistently outbid sophisticated buyers — because they do not price flood exposure — we cannot observe sophisticated buyer bids. The unsophisticated buyers in our proxy are unlikely to participate in the top market segment — as this is above their budget. Hence, we can observe the "true" sophisticated buyer price preferences by focusing on the top market segment[8].

Results are presented in Table 5. Column 1 presents flood exposure (measured as a dummy) by price segment effects for all flood zones. In line with previous results, we account for hedonic characteristics, water amenities, year-quarter by district fixed effects, relative elevation and relief, and their interaction with exposure. Again, we filter our data sample such that the border discontinuity cut-off is 200 meters, and there has to be variation in exposure classes at the district level. Although we can observe a

8. 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 buyer sophistication

	(1)		(2)		(3)		(4)	
	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top
Exposed	−0.010*	−0.021***						
	(0.004)	(0.005)						
Exposed x Per. = 1998:2007			−0.004	−0.020***				
			(0.005)	(0.005)				
Exposed x Per. = 2007:2017			−0.007	−0.018***				
			(0.005)	(0.005)				
Exposed x Per. = 2017:2023			−0.017***	−0.024***				
			(0.005)	(0.005)				
ExpType = Unembanked					−0.047**	−0.053**		
					(0.018)	(0.018)		
ExpType = Embanked					−0.009*	−0.020***		
					(0.004)	(0.005)		
ExpType = Regional					0.002	−0.047***		
					(0.009)	(0.009)		
ExpClass = Low-Med							−0.002	−0.025***
							(0.003)	(0.003)
ExpClass = High							−0.002	−0.029***
							(0.005)	(0.005)
ExpClass = Very high							−0.101***	−0.139***
							(0.018)	(0.022)
R2	0.973		0.973		0.973		0.968	
R2 Adj.	0.949		0.950		0.949		0.951	
Num.Obs.	105 600		105 600		105 413		348 981	
Hedonics	X		X		X		X	
YrQtr x District	X		X		X		X	
RelElev x ExpClass	X		X		X		X	
Relief x ExpClass	X		X		X		X	
Water Amentity	X		X		X		X	
City Centre	X		X		X		X	
BDA cut-off	<200m[a]		<200m[a]		<200m[a]		<200m	
Exposure variation	District		District		District		District	

Notes: this table presents OLS estimates with Ln(Price) as the dependent variable. The key coefficient is the interaction of an exposure measure (varies by column) and market price segments, defined by the bottom and top 50th percentiles of yearly transaction prices per district (limited to districts with ≥50 observations per year). We follow our main model specification and control for non-interacted price segments. Column 1 reports exposure by price segment coefficients, capturing general exposure pricing by segment. Column 2 introduces a triple interaction (exposure by price segment by transaction period) to assess segment-specific exposure effects over time. Column 3 interacts flood zones with price segments, merging primary and secondary flood zones into "embanked" for brevity. Column 4 interacts price segments with flood exposure categories, combining very low, low, and medium exposure into "Low-Med". In all columns, unexposed observations serve as references. 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. [a] We slightly modify our border discontinuity specification by using the maximum distance between exposed and unexposed properties rather than the flood zone.

significant price effect in both the bottom and the top price segments, the effect appears much stronger for the top segment. The large price effects for this more sophisticated market segment suggest that well-informed buyers indeed drive the observed price effect.

To examine if this sophistication effect varies over time, we apply a triple-interaction in column 2. We can observe that exposure is significantly priced in all periods for the sophisticated market segment. On the other hand, significant price effects only show in the latest period for the less sophisticated market segment. The pattern suggests that changes in price effects are mainly driven by this less sophisticated part of the market. We examine if the sophistication hypothesis holds in different flood zones by interacting the market segment measure with flood types in column 3. We can observe that exposure pricing in unembanked areas is highly similar for both sophistication groups. This finding makes sense intuitively, as it is quite obvious that unembanked areas are at risk. This risk might be less clear for embanked and regional flood zones, where we indeed observe different pricing effects. For the embanked flood zones, pricing effects are stronger and more significant for the sophisticated market segment. For regional flood zones, observe no pricing at all for the bottom segment, but rather high discounts for the top segment.

6 Discussion & Conclusion

6.1 Economic Impact

To translate our microeconomic findings into macroeconomic implications, we use a back-of-the-envelope calculation estimating total value loss due to flood hazard exposure. This should provide a general overview of how much the market is prepared to spend to mitigate flood risk. Moreover, we consider four scenarios using elevated and alleviated flood exposure levels, as well as altered climate risk perceptions. These scenarios should provide policymakers and institutions with an indication of potential future developments and market outcomes.

To obtain a macroeconomic estimate, we use our residential transaction data to estimate the market values of all single-family properties in the Netherlands (using the Basic Administration of Addresses and Buildings as a baseline). Specifically, we fit the transaction data to the following simplified hedonic model:

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

in which α is a constant intercept; V is building volume; γ_y are building construction period fixed effects; η_{tl} are year-quarter 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 Q4 2022.

Using the same approach as in our empirical design, we associate each building with a flood hazard exposure value. In turn, we can estimate value loss due to flood exposure by multiplying estimated property values with the relevant flood exposure discount rate — given the level of flood hazard. This approach might underestimate/overestimate actual value losses in two ways. First, the simplified model hedonic model estimates property prices rather crudely. If properties with flood exposure indeed have higher water amenity values, their prices might be underestimated. Second, prices already incorporate flood exposure. Since we do not account for this, price estimates of exposed properties might be overestimated — as they are based on values of both exposed and unexposed observations. We use Figure 3b 2016:2023 as inputs for exposure discount rates (this corresponds with 1.3%, 1.3%, 2.1%, 3.0%, and 7.9% for very low, low, medium, high, and very high exposure respectively).

Multiplying these discount rates with associated property values and their given exposure levels yields a total flood risk price effect of approximately €21.53 billion. Hence, despite continuous adaptation efforts, flood exposure considerably reduces the value of the Dutch single-family housing stock. To estimate the marginal effect of climate change, we estimate what the value loss would have been given the 1998:2007 discounts. These correspond to 0%, 1%, 1.1%, 1.1% and 6.7% for very low, low, medium, high, and very high exposure respectively. Again, we use 2022 property price estimates and now derive a total value loss of €10.35 billion. This value illustrates the value loss in the "absence" of climate change. Comparing the two estimates, we observe that the total costs of flood exposure have more than doubled due to additional risk induced by climate change, and despite continuous adaptation efforts.

In addition to understanding the value loss from flood risk, both in the absence and presence of climate risk, a key question is what discounts would look like in the absence of adaptation. This would allow us to draw conclusions on whether the annual investments in flood defenses are worthwhile — at least from an economic point of view. Unfortunately, we cannot observe an alternative scenario without additional adaptation. Hence, we do not know what discounts could have been in a counterfactual world with investment in dikes etc. To still provide some intuition, we consider the total value at risk and potential value loss (gains) due to worse (improved) adaptation. For the value at risk, we simply take the sum of all exposed property price estimates. For the reduced adaptation scenario, we crudely assume

that in the absence of dike maintenance, all embanked properties will become "very highly" exposed (corresponding with the 9.6% discount). We do not expect notable differences for unembanked and regional areas that have more limited protection to begin with, and retain the observed discount in Table 4 for unembanked areas and Table 3 for regional flood zones. For improved adaptation, we keep secondary dike areas and regional flood zones at 0% discounts and assume 1% discounts for unembanked and primary dike areas. The intuition is that discounts seem to persist despite extremely small risk levels as we observed in Table 3. The 1% discount matches the "very low" exposure price effect that might be achieved for all unembanked and primary dike areas due to improved adaptation and by embanking unprotected areas. Last, we consider an alternative scenario in which all actors are well-informed. To do so, we apply the "sophisticated" price effects to the entire housing market.

Table 6: Macroeconomic value loss due to flood risk exposure

	Real value loss	No climate change	Total value exposed	Low adaptation	High adaptation	High awareness
Unembanked	0.54	0.30	21.40	1.01	0.21	0.71
Primary	15.34	7.03	734.59	70.52	7.35	20.10
Secondary	1.68	1.03	109.33	1.68	0.00	2.73
Regional	0.13	0.07	5.46	0.13	0.00	0.16
Mixed	3.86	1.93	184.46	17.50	1.82	4.91
Total	**21.53**	**10.35**	**1,055.25**	**90.83**	**9.38**	**28.61**

Notes: This table presents aggregated flood exposure price effects (in € billion) for five scenarios. *Real value loss* estimates contemporaneous price effects and is calibrated with 2016:2023 coefficients from Figure 3b. *No climate change* estimates a counterfactual scenario in which price effects have remained constant and are calibrated with coefficients from Figure 3b using 1998:2007 periods. *Total value exposed* estimates the total value at risk (this is equivalent to applying a discount value of 100% for all properties that are exposed to flood risk). *Low adaptation* estimates a scenario with worsened adaptation conditions. It uses the 2016:2023 coefficients from Figure 3b for secondary and regional areas and the 9.6% discount from Table 3 for unembanked, primary, and mixed flood zones. *High adaptation* estimates a scenario with improved adaptation conditions. It uses 1% discounts from Figure 3b for unembanked, primary, and mixed flood zones and 0% discounts for secondary and regional flood zones. *High awareness* estimates a scenario where market participants are well-informed and is calibrated with results on "sophisticated" coefficients from Table 5 column 4 (2.5% for 'low' to 'medium' exposure, 2.9% for 'high' exposure, and 13.9% for 'very high' exposure).

An overview of the macroeconomic price effects estimates is presented in Table 6. We estimate the total value at risk to be about €1.1 trillion. Given this significant exposure, actual adaptation spending of approximately €8 billion per year — representing a present value of €296 billion at current Dutch 10-year bond yields of 2.7% — seems quite modest. However, homes might not lose their entire value in the absence of adaptation. Using the inputs for our "low adaptation" scenario, we estimate a total value loss of €91 billion. This is more than four times the "real" value loss that we observe. However, the amount is still considerably lower than the estimated present value of adaptation spending and

suggests over-investments in adaptive measures (but of course, we note that the collective defense system also protects assets other than single-family houses, which are not considered here). In the "high adaptation" scenario, we estimate a total value loss of €9.38 billion. This is considerably less than the "real" estimated value loss and more in line with the "no climate change" scenario. Last, the "high awareness" scenario indicates a substantial increase in value loss of €28.6 billion. Better information provision might therefore lead to substantial change in the housing market.

6.2 Conclusion

This paper 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 1.3% discount, compared to unexposed properties. The discounts become stronger as flood risk exposure increases. We only observe price effects in unembanked and primary dike areas, with price effects driven primarily by sophisticated buyers. Moreover, flood risk discounts across all exposure categories increase over time. Our collective results suggest that the Dutch housing market incorporates flood exposure, at least to some degree, in property prices. This discount suggests that homebuyers are not fully confident that the government can mitigate all risk, or compensate them entirely for potential loss or nuisance from flooding.

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. In 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, e.g. through "underwater" mortgages or significant declines in household wealth.

The presence of a flood exposure discount is in contrast with popular views that speak of a "flood risk awareness gap", and high levels of trust in the government to mitigate climate risks (OECD 2014; Bani et al. 2024). At the same time, 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, Roy, and Filatova (2023). The former identifies residential price discounts of 1% in primary dike exposure zones. Our 1.7% 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 upward-sloping exposure effects, using more recent data leads an increase in the average effect. The study of Mutlu, Roy, and Filatova (2023) identifies a 5.6% pre-flood event discount in an unembanked high exposure area between 1990-1993. This discount aligns with the "very high" exposure effect that we observe for the 1998:2007 period (approximately 6%).

Compared to sea level rise discounts observed in the US, the price effects observed in the paper are quite modest. For example, Bernstein, Gustafson, and Lewis (2019) find a 4% discount for properties exposed to sea level rise. For properties that might be affected within the next century, they find even larger price effects, of 7%. Baldauf, Garlappi, and Yannelis (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 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 rates of the "lower exposure" classes. These lower discount rates are striking, as flood exposure in the Netherlands already threatens properties today, rather than only 50 or 100 years from now. We interpret these relatively low exposure discounts as evidence that home buyers in the Netherlands have more faith in present and future flood risk adaptability or government compensation, as compared to consumers in the US.

Indeed, the collective water defense approach, compensation schemes, institutional experience, limited flood duration, and adaptation feasibility might explain the relatively low discounts that we observe. Large-scale protection programs with continuous funding provide markets with confidence about the future. Since most of the large-scale protection programs are funded nationally, homeowners experience little adaptation costs while still gaining the benefits from reduced exposure and water accessibility. This feeling of financial safety is further strengthened by disaster compensation. Even though the flood protection system can not guarantee absolute safety, compensations in events where

calamities do happen further shift the costs of exposure from individuals to the collective. Along with this, experience with living in flood-exposed areas might reduce anxiety and strengthen beliefs in the possibility of adaptation. It is also important to note that flood durations can differ considerably. Storm surges and river floods are mostly temporal, whereas sea level rise and dike breaches are long-lasting. The different time horizons and hazards make it difficult to compare these discounts directly. Last, adaptation opportunities and feasibility can play an important role. It is, for example, not as expensive to protect against overflowing from a river, as compared to protect an entire coast from sea level rise (Dottori et al. 2023).

While the collective approach against flood risk seems to work — exposed areas remain desirable and only limited flood risk discounts are observed — there are some concerns. Collective adaptation programs are effective, as single defenses protect many assets. But simultaneously they can incentivize free-riding behavior if contributions do not differentiate on place-specific risks. Once people enjoy additional water amenities without paying extra, they are more likely to concentrate in such places than in safe areas. This can stimulate path-dependent development in sub-optimal places, causing even higher needs for future adaptation (Ouazad and Kahn 2025). National compensation programs and unclear marginal insurance costs of flood exposure can strengthen such outcomes. Hence, the collective Dutch approach raises a solidarity issue. Local taxes such as those raised by water-boards might partly mitigate free-riding behavior if they link adoption contributions to exposure.

Our results yield important implications for other geographies prone to flood risk — specifically river deltas. Despite the fact that these are challenging geographies, policymakers 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 4: Damage Function

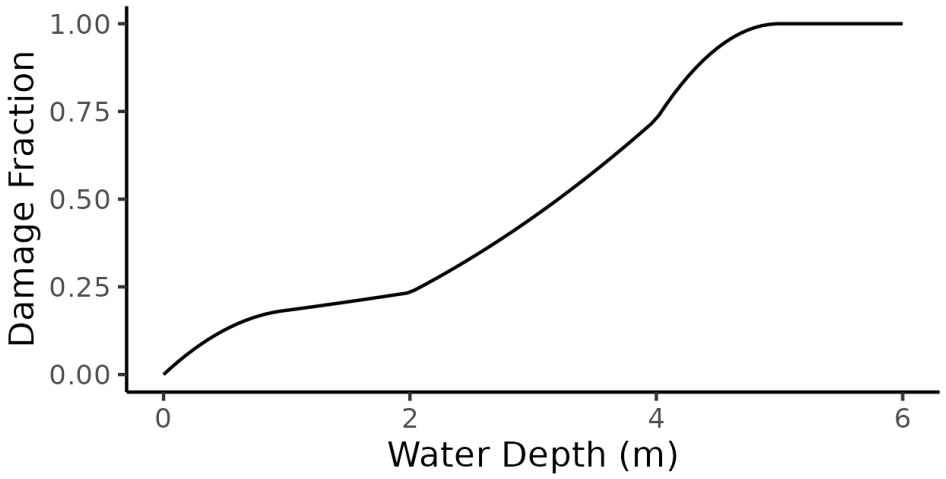


Table 7: Summary Statistics — Complete

Characteristic	Unexposed N = 810,546	Unembanked N = 8,053	Primary N = 519,490	Secondary N = 82,085	Regional N = 3,062	Mixed N = 141,988
Numeric — Mean (SD)						
Price (€ x1000)	252 (126)	237 (102)	248 (113)	255 (126)	242 (104)	258 (120)
Days on market	132 (227)	159 (251)	128 (218)	117 (193)	157 (254)	113 (179)
Volume (m3)	398 (117)	430 (141)	380 (105)	372 (90)	414 (112)	367 (93)
Parcel (m2)	243 (156)	269 (181)	202 (129)	191 (117)	266 (153)	183 (111)
Abs. elevation (m)	14 (21)	17 (14)	2 (4)	-1 (5)	16 (16)	-1 (2)
Rel. elevation (cm)	6 (7)	6 (12)	6 (7)	6 (7)	6 (8)	7 (7)
Relief (cm)	11 (12)	18 (23)	9 (10)	9 (9)	11 (15)	10 (8)
Inundation (m)	0.00 (0.00)	0.98 (0.78)	1.70 (1.03)	0.78 (0.73)	0.40 (0.36)	1.69 (1.12)
Flood prob. (‰)	0.00 (0.00)	12.26 (24.05)	2.51 (4.06)	0.68 (0.81)	10.10 (16.73)	2.57 (4.26)
Hazard (x1000)	0.00 (0.00)	1.66 (4.20)	1.11 (2.47)	0.09 (0.12)	1.01 (1.94)	0.98 (1.33)
Categorical — %						
Property type						
Corner	18	14	21	22	15	22
Detached	12	17	7.2	6.1	12	4.5
Row house	41	32	52	56	37	59
Semi-detached	26	33	17	13	33	12
Terraced house	2.7	3.9	2.4	2.4	2.9	2.2
Quality indoor						
Bad	2.4	3.0	1.8	1.8	1.7	1.9
Mediocre	12	14	10	10.0	10	10

	Unexposed	Unembanked	Primary	Secondary	Regional	Mixed
Good	74	72	76	77	76	77
Great	12	11	12	11	12	11
Quality outdoor						
Bad	0.8	1.2	0.6	0.6	0.6	0.6
Mediocre	10	13	9.0	7.6	9.4	8.1
Good	78	77	80	82	79	81
Great	10	9.5	11	9.9	11	10
Monument						
TRUE = 1	0.4	1.0	0.3	<0.1	<0.1	0.2
Constr. period						
<1906	3.7	8.8	3.4	1.2	1.1	1.5
1906-1930	12	9.5	7.8	6.1	4.2	7.4
1931-1944	8.8	6.6	5.4	3.8	3.2	5.3
1945-1959	9.2	10	5.3	5.4	15	5.3
1960-1970	15	10	13	15	13	15
1971-1980	18	17	19	22	18	22
1981-1990	14	17	19	24	16	21
1991-2000	12	12	18	14	26	14
2001-2010	5.7	6.8	8.0	7.3	2.3	7.1
2011-2020	1.7	1.8	1.9	1.6	0.9	1.8
2021-2030	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1
< 200 m = TRUE						
River: <3m	32	28	48	50	44	55
River: 3-6m	16	13	35	41	11	48
River: 6-12m	28	18	58	77	53	78
River: 12-50m	14	12	26	35	40	33
River: 50-125m	1.0	12	2.7	2.5	1.1	3.2
River: >125m	0.5	12	0.7	0.4	0	0.3
Lake: <0.1mln m^2	27	31	32	32	36	36
Lake: 0.1:1mln m^2	2.6	2.3	4.3	6.2	1.3	4.5
Lake: 1:10mln m^2	0.5	0.9	1.1	2.8	0.8	1.5
Lake: >10mln m^2	0.3	0.4	<0.1	0.2	0	<0.1
Harbor: <10k m^2	0.4	2.1	0.6	0.8	<0.1	0.5
Harbor: >10k m^2	1.0	11	1.1	0.4	0.8	0.8
sea	<0.1	<0.1	<0.1	0	0	<0.1

Table 8: General flood exposure price effects — Complete

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposed	−0.011***	−0.018***	−0.021***	−0.021***	−0.018***	−0.015***	−0.013***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Building Volume	0.002***	0.002***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Parcel Surface	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volume × Surface	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Relief		−0.027***	−0.035***	−0.036***	−0.035***	−0.041***	−0.035***
		(0.003)	(0.004)	(0.004)	(0.007)	(0.007)	(0.009)
RelElev		0.088***	0.086***	0.076***	0.105***	0.109***	0.092***
		(0.004)	(0.005)	(0.005)	(0.008)	(0.009)	(0.011)
Relief × Exp = VL		0.011	0.020	0.003	−0.004	0.000	0.003
		(0.013)	(0.017)	(0.020)	(0.021)	(0.021)	(0.026)
Relief × Exp = L		0.052***	0.019+	0.015	0.004	0.018	0.004
		(0.008)	(0.011)	(0.012)	(0.014)	(0.014)	(0.017)
Relief × Exp = M		0.060***	0.074***	0.068***	0.061***	0.070***	0.070***
		(0.007)	(0.009)	(0.009)	(0.011)	(0.011)	(0.014)
Relief × Exp = H		0.027***	0.025*	0.037**	0.034**	0.052***	0.043*
		(0.008)	(0.012)	(0.012)	(0.012)	(0.014)	(0.018)
Relief × Exp = VH		0.096***	0.047	0.060	0.050	0.059	0.030
		(0.016)	(0.041)	(0.041)	(0.042)	(0.044)	(0.055)
RelElev x Exp = VL		0.065***	0.054*	0.035+	0.005	−0.006	0.012
		(0.016)	(0.021)	(0.021)	(0.023)	(0.024)	(0.029)
RelElev x Exp = L		0.038***	0.023*	0.031*	0.007	0.006	0.029
		(0.009)	(0.012)	(0.012)	(0.015)	(0.015)	(0.018)
RelElev x Exp = M		0.007	0.010	0.012	−0.018	−0.018	−0.002
		(0.008)	(0.010)	(0.010)	(0.013)	(0.014)	(0.018)
RelElev x Exp = H		0.008	0.003	0.000	−0.025+	−0.023	0.009
		(0.010)	(0.012)	(0.012)	(0.014)	(0.016)	(0.021)
RelElev x Exp = VH		−0.023	−0.121*	−0.078	−0.106+	−0.123*	−0.164+
		(0.030)	(0.057)	(0.055)	(0.056)	(0.062)	(0.086)
R2	0.922	0.922	0.946	0.954	0.958	0.960	0.966
R2 Adj.	0.910	0.910	0.921	0.929	0.932	0.933	0.935
Num.Obs.	1 565 224	1 565 224	1 565 224	1 565 224	1 007 902	912 672	670 788
Hedonics	X	X	X	X	X	X	X
YrQtr x District	X	X	X	X	X	X	X
Water Amenity			X	X	X	X	X
City Amenity				X	X	X	X
BDA cut-off					<1,000m	<500m	<200m
Exposure variation					District	District	District

Notes: This table presents equal results as Table 2, but includes all control variables for completeness. *VL*,*L*,*M*,*H*, and *VH* indicate 'very low', 'low', 'medium', 'high', and 'very high' flood exposure categories respectively.