

Framing Flood Risk

How reference points shape
housing market behaviour in
the Limburg river area

MSc Thesis

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FRAMING FLOOD RISK: HOW REFERENCE POINTS SHAPE HOUSING MARKET BEHAVIOUR IN THE LIMBURG RIVER AREA

Master thesis submitted to Delft University of Technology in partial fulfilment
of the requirements for the degree of

MASTER OF SCIENCE

Complex Systems Engineering and Management
Faculty of Technology, Policy and Management
Delft University of Technology

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Thesis defence date: 15 October 2026

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Preface

After six months of work, this thesis marks the completion of my MSc in Complex Systems Engineering and Management and the end of my educational journey in Delft. During this research, I had the opportunity to explore how people respond to flood risk when making housing decisions and how these individual choices can shape wider housing-market outcomes. The project allowed me to combine several of my favourite topics and research methods introduced during my studies at TU Delft, namely behavioural economics, climate change and agent-based modelling, in a way that was both challenging and rewarding.

I would like to thank my supervisors, Tatiana Filatova, Martijn Warnier and Asli Mutlu, for their guidance, constructive feedback and support throughout the research process. I really appreciated their flexibility, understanding and encouraging words during the early stages of the project, which gave me greater peace of mind and time to work through the research at my own pace. I am particularly grateful to Asli Mutlu for providing the base housing-market model and accompanying data, which formed a great foundation for the behavioural extensions developed in this thesis.

I would also like to thank my friends and family for their encouragement and patience throughout the graduation process. I am very grateful to my friends for the shared study sessions and conversations, for putting up with my occasional moodiness during the difficult early stages and for providing well-appreciated distractions along the way. Their support and company brought a welcome balance throughout the research process.

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Delft, October 2026*

Executive Summary

Flooding can cause serious damage to homes, but its effects extend beyond repair costs. Flood risk can influence where people live, how much they are willing to pay for a property and which households remain exposed. These decisions are especially relevant in the Netherlands, where continued housing demand places pressure on both safe and flood-prone areas.

Conventional economic models often assume that households assess flood risk by combining the probability of flooding with the expected financial damage. In reality, people may respond differently. Their decisions can depend on the benchmark against which they compare possible losses, their previous flood experiences and their expectations of compensation or future property values. Consequently, households facing the same objective flood probability may evaluate a property differently.

This research examines how alternative ways of evaluating flood losses affect housing decisions and wider market outcomes in the Limburg river area. It applies prospect theory, which explains decision-making under uncertainty and possible losses. A central concept is the reference point: the benchmark used to determine whether an outcome is perceived as a gain or loss. Ten formulations are examined, including objective expected losses, individual flood events, expected future property value, different levels of anticipated financial protection and recent, moderate or distant flood experiences.

These mechanisms were introduced into an existing model of the Dutch housing market. The model represents individual households and properties and simulates how buyers search for affordable homes, evaluate listings, place bids and complete transactions. Households differ in income and in how strongly they respond to losses and flood probabilities. Their decisions therefore reflect both purchasing power and behavioural differences.

Each reference-point formulation was tested under annual flood probabilities of 2%, 3% and 5%, as well as under medium and high housing demand, resulting in 60 scenarios. Every scenario was repeated 50 times to account for random variation. The analysis compared transaction prices, housing utility and market activity inside and outside the flood zone. It also examined whether households with different incomes and behavioural characteristics became concentrated in particular locations. This approach shows how individual housing decisions collectively affect market outcomes and the distribution of flood exposure.

The results show that flood risk affects both housing-market performance and the distribution of households. Flood-prone properties generally had lower transaction prices, lower utility and a smaller fraction of properties sold than properties outside the flood zone. These differences generally increased as objective flood probability rose. However, differences between the reference-point formulations became smaller at 5% annual flood probability for final market prices and spatial sorting patterns. At this relatively high risk level, flood exposure was already evaluated negatively under nearly every formulation, leaving less room for the choice of reference point to alter outcomes.

The way households evaluated flood losses nevertheless produced meaningful differences, particularly at 2% and 3% flood probability. Subjective evaluation through prospect theory led to larger differences between flood-prone and non-flood-prone properties than objective expected losses. Expected future property value produced broadly similar outcomes and did not consistently increase or reduce the flood-related penalty. Anticipated financial protection reduced perceived losses, although only protection of 80% lowered market differences below those produced by objective risk perception. Outcomes based on distant flood experience were closest to the objective-risk baseline.

Flood risk also affected where different households lived. Lower-income households were increasingly concentrated in flood-prone areas, while wealthier households were able to purchase their way to safety. This separation was stronger under high housing demand. Differences in probability weighting and loss aversion also contributed to sorting. Households that responded more strongly to flood probabilities and losses were generally more common outside the flood zone. Probability weighting had a clearer effect than loss aversion.

These findings show that flood policy should consider both physical risk and how households understand that risk. Clear, consistent and repeated information on flood risk and potential damages can help buyers make informed choices. Public flood defences can reduce risk for all residents and may particularly benefit lower-income households that have fewer housing alternatives. Financial protection can also limit household losses, but compensation arrangements should be communicated clearly so that expectations remain realistic.

Future research should examine which reference points households actually use when purchasing homes under flood risk. The model should also be tested at lower flood probabilities, in other regions and cultures, and with property-level protection measures. Overall, the study shows that subjective evaluations of flood risk can influence prices, market activity and which households ultimately remain exposed.

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Problem statement

Due to human-induced climate change, flooding and extreme weather events are becoming increasingly frequent and severe across both coastal and inland regions (IPCC, 2023; Ulloa et al., 2025). These developments pose growing challenges for housing markets and regional economies, particularly in already constrained European housing systems. Flood risks can damage housing stock, disrupt residential stability, and affect property values, thereby influencing affordability, mobility, and overall market dynamics (Filatova & Bin, 2013; Caloia et al., 2023).

Housing markets exposed to environmental risk provide a relevant context for examining how individuals make decisions under uncertainty. Housing decisions are high-stakes and long-term, requiring households to evaluate uncertain future risks. Traditional models, particularly expected utility theory, assume that individuals rely on objective probabilities and final wealth outcomes. However, empirical evidence shows that behaviour systematically deviates from these assumptions, especially in low probability, high impact settings such as natural hazards (Barberis, 2013). Instead, individuals often rely on subjective beliefs and past experiences when assessing risk.

Prospect theory provides a more behaviourally realistic framework for analysing such decision-making. Individuals evaluate outcomes as gains or losses relative to a reference point, while also exhibiting loss aversion and probability weighting (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). The choice of reference point is therefore central, as it determines how outcomes are framed and how strongly individuals respond to potential losses. In housing markets, this implies that property valuation depends not only on objective risk levels, but also on how individuals interpret and frame those risks.

Reference-dependent behaviour has been widely observed in housing markets. Homeowners anchor expectations to past purchase prices and exhibit loss aversion when market values fall below this level, leading to higher asking prices and longer time on the market (Genesove & Mayer, 2001). Similar effects are observed in commercial real estate, where anchoring influences pricing decisions even among experienced investors (Bokhari & Geltner, 2011). These findings highlight that market outcomes are shaped not only by fundamentals, but also by behavioural biases.

Understanding these behavioural responses is important because they directly influence housing market dynamics. Individual decisions aggregate into broader patterns affecting housing prices, spatial distribution, and residential mobility. In flood-prone regions, these processes shape how risk is reflected in housing markets and how communities respond to increasing environmental pressures. As climate risks intensify, these dynamics become increasingly relevant for both market functioning and societal resilience.

The problem addressed in this research therefore lies at the intersection of climate risk, individual decision-making, and housing market dynamics. It reflects a complex socio-technical system in which physical hazards, behavioural responses, institutional arrangements,

and economic processes interact over time. Understanding these interactions is essential for anticipating housing market responses and supporting effective policy under uncertainty.

This perspective aligns closely with the interdisciplinary character of the Complex Systems Engineering and Management (CoSEM) MSc programme at TU Delft, where complex societal challenges are approached through a systems lens integrating technical, economic and social dimensions. By combining behavioural economics with housing market analysis under flood risk, this research reflects the CoSEM values of systems thinking, analytical rigour and societal relevance.

This research gradually develops from problem definition and theoretical grounding towards model implementation and analysis. Following the introduction, the literature review identifies key concepts and empirical findings concerning flood risk, behavioural decision making and housing markets. The research question and sub-questions are then formulated, followed by an explanation of the research approach, methods, data sources and analytical tools. Subsequent chapters describe prospect theory, the alternative reference point formulations, model adaptations and scenario design. The model is then evaluated through verification and validation before the simulation results are presented and synthesised across housing market outcomes and household spatial sorting. The model limitations and directions for future research are subsequently discussed, after which the conclusion answers the research questions and presents the policy implications and recommendations.

Knowledge gap and research question

Flood risk is increasing across Europe, as shown by the recent flooding events of 2021, where regions of central Europe suffered economic losses of approximately \$13 billion (Aon, 2022). These events highlight how climate-induced hazards place growing pressure on housing markets and regional economies, particularly in areas exposed to riverine flooding. Beyond physical damages, flood risk introduces uncertainty into housing decisions, affecting how households evaluate properties, perceive risk, and respond to changing environmental conditions. While a substantial body of literature has examined the economic impacts of flood risk, less attention was given to the behavioural mechanisms that underlie market responses.

This literature review focuses on key concepts that form the basis for analysing housing market behaviour under flood risk, including flood risk, housing market dynamics, behavioural decision-making, and risk perception. Flood risk refers to the probability and potential severity of flooding resulting from hazards such as extreme precipitation and river overflow, combined with local exposure and vulnerability. Housing market dynamics describe how prices, supply, demand, and residential mobility respond to both economic conditions and external shocks. Behavioural decision-making captures how individuals deviate from purely rational models when evaluating risk, often relying on heuristics, reference points, and subjective beliefs (Kahneman & Tversky, 1979; Barberis, 2013). Within this framework, prospect theory provides a foundation for understanding how individuals assess gains and losses relative to a reference point, and how loss aversion and probability weighting shape decisions under uncertainty (Tversky & Kahneman, 1992).

Risk perception plays a central role in linking these concepts. Rather than responding to objective flood probabilities, households form subjective perceptions of risk that influence their housing choices and valuation of properties. These perceptions are shaped by experience, information, and contextual factors, and may lead to systematic over- or underestimation of flood risk (Mol et al., 2020; Gallagher, 2014). As a result, behavioural responses to flood risk can differ significantly from predictions based on standard economic theory. Understanding how these behavioural mechanisms interact with housing market dynamics is essential for analysing how flood risk is reflected in property values and spatial patterns of development.

Literature review method

The literature review followed a systematic and structured process to ensure a comprehensive and relevant selection of academic sources, as schematically depicted in Figure 1. Four main steps guided the procedure: identification, screening, eligibility assessment, and inclusion. Keyword search strings were formulated around behavioural decision-making, housing markets, and flood risk, incorporating terms such as prospect theory, loss aversion, and risk perception. These search strings were applied in the Scopus database using Boolean operators to refine the results. The initial search included titles, abstracts, and keywords, after which filters were applied to restrict the selection to English-language journal articles within the fields of economics, social sciences, and environmental sciences. Titles, abstracts, and keywords were reviewed to narrow the set based on relevance to the research topic.

Identification	Keyword search strings in Scopus: 1. (housing OR "real estate") AND "flood risk" AND ("decision making" OR "bias" OR "perception") 2. ("prospect theory" OR "loss aversion") AND (housing OR "real estate") 3. ("flood risk" OR flooding) AND ("risk perception") AND (housing OR homeowner)
	Database: Scopus N = 147 + 135 + 127 = 409 Title – Abstract – Keywords
Screening	Limited to: 1.) Fields: Environmental Science, Social Sciences; Type: Article; English; Keywords: Housing, Housing market 2.) Fields: Economics, Social Sciences; Type: Article; English; Keywords: Loss aversion, prospect theory, housing market 3.) Fields: Economics, Social Sciences; Type: Article; English; Keywords: Housing market, Flooding, Risk perception/assessment N = 38 + 47 + 46 = 131
	After screening of title N = 26 + 32 + 31 = 89
Eligibility	After screening of title + abstract + keywords and duplicate removal N = 15 + 16 + 8 = 39
	Added articles from forward/backward snowballing + recommendations N = 46
	After screening of introduction + results + conclusions: N = 21
Included	Final set of articles: N = 21

Figure 1. Literature selection process

In defining the scope of the literature review, the focus was placed on studies examining behavioural responses to flood risk in housing markets, with particular attention to decision-making processes, risk perception, and reference-dependent behaviour. Studies lacking a clear behavioural component or not directly related to housing or property markets were excluded. Rather than concentrating on a single hazard type, the review prioritised research that provides insight into how households perceive and respond to flood risk, including the role of experience, uncertainty, and institutional context. This approach aligns with the aim of understanding how behavioural mechanisms, such as loss aversion, reference points, and perception biases, influence housing market outcomes in flood-prone regions.

Table 1. Analysed literature for review

Topic/title	Authors & year
Flood risk discounts and housing market outcomes	
Changes in implicit flood risk premiums: Empirical evidence from the housing market	Bin & Landry, 2013
Flood hazards impact on neighborhood house prices: A spatial quantile regression analysis	Zhang, 2016
Flood risk information release: Evidence from housing markets around Paris	Dubos-Paillard et al., 2024
Cognitive limits of perceived flood risk on residential property values	Shi et al., 2024
Does flood risk affect property prices? Evidence from a property-level flood score	Skouralis et al., 2024
Capitalized value of evolving flood risks discount and nature-based solution premiums on property prices	Mutlu et al., 2023
Subjective risk perception and information processing	
Insights into flood risk misperceptions of homeowners in the Dutch river delta	Mol et al., 2020
Learning about an infrequent event: Evidence from flood insurance take-up in the United States	Gallagher, 2014
Longitudinal survey data for diversifying temporal dynamics in flood risk modelling	Mondino et al., 2021
Influence of flood risk characteristics on flood insurance demand: A comparison between Germany and the Netherlands	Seifert et al., 2013
Flood risk perception in the housing market and the impact of a major flood event	Hennighausen & Suter, 2020
The impact of floods on house prices: An imperfect information approach with myopia and amnesia	Pryce et al., 2011
Monetary valuation of insurance against flood risk	Botzen & van den Bergh, 2012
Modelling housing markets under flood risk	
Changing climate, changing behavior: Housing markets responses to flood risks.	Filatova & Bin, 2013
Empirical agent-based land market: Integrating adaptive economic behavior in urban land-use models	Filatova, 2014
Bridging revealed and stated preferences in flood-prone housing markets	De Koning et al., 2017
Capitalization of flood insurance and risk perceptions in housing prices: An Empirical Agent-Based Model approach	De Koning et al., 2019
Behavioural decision-making and reference dependence	
Loss aversion and seller behavior: Evidence from the housing market	Genesove & Mayer, 2001
Loss aversion and anchoring in commercial real estate pricing	Bokhari & Geltner, 2011
How to weaken the endowment effect in the housing market? The role of behavioral interventions	Tomal, 2024a
The Endowment Effect and Housing Studies: The Role of Multiple Reference Points	Tomal, 2024b

Following the initial screening, additional relevant studies were identified through forward and backward snowballing, as well as recommendations from supervisors. A final eligibility assessment was conducted by reviewing the introduction, results, and conclusions of the remaining papers to ensure strong thematic alignment and analytical contribution. The final set consists of twenty one studies that collectively capture the theoretical foundations and

empirical evidence required to analyse behavioural decision-making in housing markets under flood risk. An overview of the included articles can be found in Table 1, where they are categorised according to their thematic relevance.

The thematic search was supplemented with foundational prospect theory literature to support the interpretation and operationalisation of loss aversion, probability weighting and reference dependence.

Analysis and synthesis of articles

The reviewed literature can be understood as a sequence connecting objective flood exposure to housing market outcomes. Flood risk first becomes visible through differences in property prices and market activity. These outcomes depend on how households perceive and process risk information, how decision-making is represented in housing market models and which behavioural assumptions are used. The following synthesis therefore moves from observed flood risk discounts to subjective risk perception, modelling approaches and, finally, the role of prospect theory reference points.

Flood risk discounts and housing market responses

The empirical literature generally agrees that flood exposure reduces residential property values, but provides no single estimate of the resulting flood risk discount. This variation is analytically important because it indicates that prices do not simply reflect objective flood probability and expected physical damage. Instead, capitalisation depends on how risk is measured, communicated and perceived, as well as on previous flood experience, property characteristics and local housing market conditions. A flood risk discount should therefore be understood as the market outcome of interactions between physical exposure and household behaviour, rather than as a direct monetary measure of objective risk.

The development of these price discounts provides evidence of this behavioural component. Bin and Landry (2013) find that price differences between exposed and non-exposed properties increase following major flood events but gradually decline as the event becomes more distant. Pryce et al. (2011) explain this pattern through flood risk myopia and amnesia. Households initially respond strongly because a recent event makes the risk vivid and accessible, but give it progressively less weight when no new flooding occurs. The objective hazard may remain unchanged throughout this process. Changes in the price discount therefore reveal changes in the salience and perceived importance of risk rather than equivalent changes in physical exposure.

Evidence from Limburg supports this temporal relationship. Mutlu et al. (2023) identify a 5.6% discount for flood-prone properties before the 1993 and 1995 Meuse floods, which increased to 10.9% immediately afterwards. The discount subsequently declined and disappeared after approximately 9 to 12 years. This decline coincided with the implementation of major flood management interventions, meaning that it may reflect both fading risk salience and increased confidence in local protection. Nevertheless, the changing discount shows that housing market responses evolved considerably even though the underlying flood-prone classification remained in place.

Information can also affect capitalisation without the occurrence of a new flood. Dubos-Paillard et al. (2024) find that the release of regulatory flood risk information around Paris resulted in price discounts of approximately 3% to 7%, depending on the property type and designated risk level. However, buyers with previous flood exposure applied smaller discounts. This shows that identical information does not necessarily produce identical valuations, as existing experience influences its interpretation. Flood risk disclosure may therefore improve awareness while still generating heterogeneous market responses due to different interpretations and risk tolerances.

Discounts also differ between housing segments and levels of exposure. Zhang (2016) finds stronger effects among lower-priced homes, suggesting that average estimates can conceal important distributional differences. Using property-specific flood scores in England, Skouralis et al. (2024) report an average discount of 8.14% for exposed properties, increasing to 32.2% for properties facing very high risk. Shi et al. (2024) similarly identify discounts of 10.8% within a 1-in-100 annual flood probability zone and 4.4% within a 1-in-500 zone, but find no significant discount for properties exposed only to a 1-in-1,000 event. Their findings suggest a cognitive threshold beyond which buyers have difficulty distinguishing and pricing very small probabilities.

These estimates cannot be compared as if they measure one universal effect, since the studies differ in geographical context, risk indicators, information availability and empirical methods. Together, however, they demonstrate that flood risk is imperfectly and unevenly capitalised. Market prices reflect not only physical exposure, but also whether households notice, understand and continue to consider that exposure. Explaining variation in flood risk discounts therefore requires closer examination of subjective risk perception and how households process low-probability information.

Subjective risk perception and information processing

The variation in flood risk discounts indicates that households do not respond uniformly to objective probabilities. Instead, they form subjective perceptions from available information and how they process it. This distinction is particularly relevant for flooding, which combines a relatively small probability with potentially severe consequences and is often communicated through technical measures such as return periods.

Evidence from the Netherlands demonstrates that subjective and objective risk can differ substantially. Using survey data from 1,848 homeowners in the Dutch river delta, Mol et al. (2020) find that perceptions of flood probability and damage are influenced by objective information, including dike safety standards, and behavioural heuristics. The availability heuristic gives greater weight to risks that are easily recalled, while affective responses influence whether flooding feels personally threatening. Similar households may therefore evaluate the same exposure differently.

Flood experience is an important source of variation, but its influence changes over time. Gallagher (2014) finds that insurance uptake rises sharply following a flood and subsequently declines towards its previous level. The response extends to non-flooded communities within

the same media market, although it is weaker than in directly affected areas. Hennighausen and Suter (2020) further distinguish inundated properties from near misses within the same floodplain. Inundated properties experienced a price reduction after the event, whereas near-miss properties increased in relative value. Flooding therefore provides property-specific information rather than uniformly increasing perceived risk across an exposed area.

These temporal patterns cannot always be represented by one rate of declining awareness. Mondino et al. (2021) show that longitudinal survey data reveal diverse behavioural responses and that implementation can improve human-water models. Pryce et al. (2011) describe this temporal pattern as flood risk myopia and amnesia. They show an overall tendency for flood risk attention to increase after floods and then gradually decline, while individual responses remain heterogeneous.

Risk perception is also shaped by how losses and protection are framed. Seifert et al. (2013) find greater willingness to pay for insurance against a medium-probability, medium-impact risk in Germany than against a low-probability, high-impact risk in the Netherlands. Botzen and van den Bergh (2012) additionally show that expected government compensation reduces private insurance demand. Households thus evaluate the expected financial consequences and available protection alongside the hazard itself.

Prospect theory could help explain these findings. Under cumulative prospect theory, outcomes are evaluated as gains or losses relative to a reference point and losses receive greater weight than equivalent gains. Another important property is that small probabilities are subjectively weighted and oftentimes overestimated (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Flood decisions may consequently differ according to experience, expected compensation and the benchmark used to evaluate damage. Housing models should therefore represent heterogeneous perceptions rather than assuming identical responses to objective risk.

Reference dependence in housing and flood-risk decisions

Evidence from housing markets shows that reference points influence valuations and whether transactions occur. Genesove and Mayer (2001) find that homeowners facing nominal losses relative to their purchase price set higher asking prices and are less likely to sell. The purchase price therefore always remains behaviourally relevant. Bokhari and Geltner (2011) identify loss aversion and anchoring even among experienced commercial property investors. Their findings indicate that reference dependence is not merely a consequence of household inexperience, but a persistent feature of property valuation.

However, treating the purchase price or current ownership as the single reference point may oversimplify housing decisions. Tomal (2024b) distinguishes between price-based, ownership, locational, social and transaction-related reference points, demonstrating that several benchmarks can shape willingness to pay and willingness to accept. The same transaction can therefore be perceived as a gain relative to one benchmark and a loss relative to another. Which reference point dominates becomes as important as the degree of loss aversion itself. Tomal (2024a) shows that highlighting and visualising market-price information reduced

the WTA–WTP gap from 7.01% to 2.48%, without eliminating it. Information can thus shift the influence of competing benchmarks while reference dependence persists.

Together, these findings indicate that reference-point selection is central to explaining housing behaviour rather than a neutral modelling decision. Under flood risk, purchase prices, expected market values, anticipated compensation and previous flood experiences may all provide benchmarks. Their relative importance determines the loss against which a household evaluates a property. Two households facing identical flood probabilities may value a property differently because they perceive the probability differently or assess its consequences relative to different baselines. Reference points thus provide a behavioural link between subjective flood-risk perceptions, bids and market outcomes. Understanding how to translate these competing reference points into household decisions is therefore essential for explaining how subjective flood-risk perceptions develop into observable housing-market outcomes.

Modelling housing decisions under flood risk

The literature uses three main approaches to examine housing decisions under flood risk: hedonic price models, stated preference methods and agent-based models. Hedonic models identify how exposure is capitalised into observed prices, while surveys and choice experiments examine reported perceptions and willingness to pay. Agent-based models formalise individual decision rules and simulate how heterogeneous households produce aggregate prices, transactions and spatial patterns.

Hedonic models provide strong empirical evidence because they use realised market behaviour. Mutlu et al. (2023), for example, reveal how the flood risk discount in Limburg changed following the 1993 and 1995 floods. However, prices do not reveal why buyers applied a particular discount. A lower price may reflect perceived damage, insurance costs, limited demand, experience or confidence in public protection. Hedonic models can therefore identify capitalisation but have limited ability to isolate the behavioural process producing it.

Stated preference methods provide more direct information about perceptions and intended choices. Surveys can elicit perceived probabilities, expected damage, insurance demand and willingness to pay under controlled scenarios. However, hypothetical choices may differ from actual transactions. De Koning et al. (2017) show that stated and revealed preference estimates can diverge because individual valuations are altered through market interaction, neighbourhood effects and behavioural biases. Combining empirical observations with simulation can clarify how individual intentions become market outcomes.

Agent-based modelling is particularly suited to this task because households can differ in income, preferences, risk perception and experience. Filatova (2014) developed the RHEA model to connect spatial and hedonic data with an economic housing market in which prices emerge through interactions between buyers and sellers. Behavioural assumptions can be changed while other conditions remain constant, allowing mechanisms that cannot be isolated through observational data to be examined.

Applications demonstrate that including behaviour can materially change model outcomes. Filatova and Bin (2013) show that changing risk information and adaptive behaviour

can generate nonlinear changes in prices and spatial development. De Koning et al. (2019) find that stronger risk perception increases flood-zone price discounts, while insurance uptake can stabilise the value of capital at risk across different risk attitudes. Haer et al. (2017) similarly demonstrate that treating household adaptation as constant misrepresents flood risk by excluding feedback between perceived risk, protective investment and future damage.

Agent-based models thus provide a bridge between subjective household evaluations and observable market outcomes. Their explanatory value, however, depends on the behavioural rules imposed on agents. The reviewed literature largely treats prospect theory and changing flood risk perceptions as separate behavioural mechanisms. Models applying prospect theory generally use a predetermined reference point, such as the expectation of no flooding or wealth before a specified flood event, to study other outcomes including insurance uptake and investments in damage prevention. By contrast, empirical studies show that flood risk perception itself changes with experience, information, expected compensation and the time elapsed since a flood. These observed perception biases have not been systematically translated into alternative prospect theory reference points and compared within the same housing market model. Consequently, it remains unclear how the choice of reference point affects the way changing risk perceptions influence housing decisions and resulting market outcomes.

Research questions and knowledge gap

The reviewed literature demonstrates that behavioural biases such as loss aversion, reference dependence, and perception dynamics play a significant role in housing market responses to flood risk. While existing studies provide strong evidence on pricing effects, risk perception, and institutional influences, they typically examine these mechanisms in isolation.

In particular, alternative reference points for housing decisions under flood risk have rarely been explicitly formulated within a prospect theory framework. Existing applications generally assume a single predetermined benchmark rather than formulating and testing competing reference points based on different perception biases. Consequently, little research has systematically compared how alternative reference points influence individual decisions and resulting housing market outcomes. This gap is especially relevant in the Dutch context, where high levels of flood protection and reliance on public compensation shape risk perception and valuation. To address this gap, this study compares multiple prospect theory reference points within a unified modelling framework, leading to the following research question:

How do different prospect theory reference points influence individual housing decisions and resulting market outcomes under flood risk in the Limburg river area?

Formulating sub-questions

The formulation of sub-questions structures the research project and translates the main research question into a coherent sequence of analytical steps. Sub-questions fulfil both an efficiency function by specifying which knowledge is required and a steering function by guiding the research activities needed to obtain that knowledge. In line with the modelling approach adopted in this study, the sub-questions are formulated to progressively build insight

into the socio-technical system in which flood risk, housing market dynamics and behavioural decision-making interact.

The first sub-question focuses on developing a conceptual understanding of the system:

How do flood risk, housing market dynamics, and individual decision-making interact in riverine regions under increasing climate pressure?

This sub-question supports system delineation by identifying key actors, mechanisms, and feedbacks that characterise the Limburg river area and results in a conceptual system representation that forms the basis for model design. System-oriented analysis is a common starting point in studies of complex socio-economic systems, as it provides the foundation for modelling interacting components and their dynamics.

Building on this system understanding, the second sub-question narrows the focus to behavioural mechanisms within housing markets:

How do behavioural factors, including risk perception, loss aversion, and reference dependence, influence housing decisions under flood risk?

This sub-question targets the decision-making processes of households and specifies which behavioural assumptions are incorporated into the model. It ensures that individual decision-making is grounded in behavioural economic theory and empirical insights rather than purely rational assumptions.

The third sub-question introduces prospect theory as the central analytical framework:

How can different prospect theory reference points for buyers be defined and operationalised in housing market decision-making under flood risk?

This sub-question has a design-oriented character and supports the translation of theoretical concepts into model components. It focuses on specifying alternative reference points and how they influence perceived gains and losses, enabling comparison between different behavioural assumptions.

The final sub-question is integrative and addresses market-level outcomes:

How do differences in reference points and behavioural assumptions influence housing market outcomes under flood risk in the Limburg river area?

This sub-question synthesises the outcomes of the previous steps by linking individual decision-making to aggregate market dynamics such as price formation and spatial patterns. Such generative reasoning, where system-level outcomes emerge from individual behaviour, is central to simulation-based research on complex systems.

Together, these sub-questions form a logical sequence in which each step builds on the previous one. This structure ensures coherence between the research objectives, the modelling approach, and the main research question.

Research approach and methods

Introduction

Climate change is increasing the frequency and severity of flooding events, with growing consequences for housing markets and regional economies. The problem introduction described how flood risk affects property values, household decisions, and spatial development patterns. Particular attention was given to riverine regions, where exposure to flooding is rising while housing markets remain constrained. The Limburg river area in the Netherlands was introduced as a relevant case due to its flood exposure and socio-economic characteristics.

Subsequently, the literature review examined behavioural decision-making, flood risk perception, and housing market responses. This review showed that housing market outcomes are shaped not only by objective flood risk but also by behavioural mechanisms such as loss aversion, reference dependence, and evolving risk perceptions. It further highlighted that these mechanisms are often studied in isolation, with limited integration within a unified framework. This gap motivates the present research focus on how different prospect theory reference points influence housing decisions and resulting market outcomes under flood risk.

Choosing a research approach

The research problem addressed in this thesis concerns the functioning of a complex socio-technical system in which flood risk, housing market dynamics, and behavioural decision-making interact over time (Holling, 2001; Filatova, 2014). The literature review demonstrated that while the economic impacts of flood risk and housing market responses are increasingly studied, there is limited understanding of how behavioural mechanisms such as reference dependence, loss aversion, and risk perception shape market outcomes. This type of problem requires a research approach capable of analysing interactions between heterogeneous actors, capturing feedback mechanisms, and exploring system-wide consequences under uncertainty. For these reasons, a modelling approach is selected as the most appropriate research strategy (Creswell & Creswell, 2018).

A modelling approach is particularly suitable when the objective is to analyse how individual decision-making processes translate into aggregate outcomes through interaction effects (Grimm et al., 2005). In the context of housing markets under flood risk, outcomes such as price formation, spatial sorting, and market dynamics emerge from the combined decisions of households responding to perceived risks and economic constraints. These processes are difficult to observe directly and cannot be fully captured using purely qualitative approaches or static econometric techniques. Modelling allows for the formalisation of behavioural assumptions, including prospect theory mechanisms, and enables the exploration of causal relationships under different system configurations (Railsback & Grimm, 2019).

Agent-based modelling choice

Within this modelling paradigm, agent-based modelling is particularly suited to the analysis of socio-technical systems, as it explicitly represents individual actors and their

interactions (van Dam et al., 2013). Agent-based models allow households to differ in characteristics such as income, location preferences, and risk perception, which is essential for capturing behavioural heterogeneity in housing markets. This is particularly relevant when incorporating prospect theory, where decision-making depends on subjective reference points and perceived gains and losses. By simulating interactions between households under varying flood risk conditions and reference point specifications, the model can generate emergent housing market patterns that reflect the behavioural complexity identified in the literature.

Agent-based modelling is preferred to statistical approaches because the research question concerns the mechanisms through which individual evaluations produce market-level effects. Hedonic price models can estimate associations between flood exposure and transaction prices, but they do not represent search, bidding, failed transactions or feedback between household choices and available properties. Stated-preference methods can reveal how respondents evaluate hypothetical risks, although they do not reproduce the repeated interactions through which prices and residential sorting emerge. Agent-based models can connect these analytical levels.

Filatova (2014) demonstrates this through the RHEA model, which combines empirical hedonic functions with heterogeneous buyer and seller decisions so that prices and spatial patterns emerge endogenously. De Koning et al. (2017) further show how revealed and stated preferences concerning flood risk can be integrated within an empirical agent-based housing market. Haer et al. (2017) demonstrate that excluding household behaviour and its feedback with flood risk can substantially misrepresent aggregate risk. This is directly relevant because changing a prospect theory reference point initially alters household utility and bidding, after which transactions, prices and residential patterns emerge through market interactions. Controlled scenario experiments can therefore isolate the consequences of each behavioural formulation while retaining an identical market structure.

The model is therefore used as a computational laboratory rather than as a forecasting tool. Its purpose is to examine how alternative behavioural assumptions change individual decisions and aggregate market outcomes under otherwise comparable conditions. This comparative design supports an exploratory and explanatory research objective, as it seeks to identify behavioural mechanisms and trace their consequences across system levels rather than predict exact future market developments (Creswell & Creswell, 2018). The findings are consequently interpreted in terms of relative differences between scenarios. Since the model necessarily simplifies household behaviour, housing-market processes and the physical representation of flood risk, individual output values are not treated as definitive forecasts. Their value instead lies in revealing whether the identified relationships remain consistent across different reference-point formulations and flood-risk conditions.

Finally, this modelling approach aligns with the intended audience of the research. Policymakers and planners in flood-prone regions require insight into how behavioural responses to risk may influence housing market outcomes under uncertainty. A transparent and well-structured model can support such decision-making by clarifying behavioural mechanisms, identifying potential unintended effects, and highlighting how different

assumptions about reference points may lead to different outcomes. In this way, the research contributes to a better understanding of how behavioural dynamics shape housing markets in flood-prone riverine regions.

Research methods to answer sub-questions

This section explains how each sub-question is addressed through a coherent set of research activities aligned with the modelling-oriented research approach. The methods focus on representing behavioural decision-making in housing markets under flood risk in a systematic and transparent way.

The first sub-question, which examines interactions between flood risk, housing markets, and individual decision-making in riverine regions, is addressed through conceptual modelling and system analysis. The RHEA (Risks and Hedonics in Empirical Agent-based land market) framework developed by Filatova (2014) is used as an analytical reference to structure interactions between households, housing supply, and spatial dynamics. The framework is adapted to the Dutch riverine context in Limburg and incorporates local housing characteristics, including floor area, number of rooms and distance from the property to the river (Mutlu & Filatova, 2026).

The second sub-question, focusing on behavioural mechanisms, is addressed by defining behavioural rules and alternative reference points for household decision making. Empirical findings from the literature inform how risk perception, previous experiences, expectations, reference dependence and decision making under uncertainty influence housing choices. These mechanisms provide the behavioural foundation required to represent housing decisions according to prospect theory principles.

The third sub-question addresses the implementation and parameterisation of prospect theory reference points within the modelling framework. Alternative reference points are incorporated into buyers' decision rules, while parameter values derived from the literature introduce heterogeneity in decision making. Scenario design then enables systematic comparison between behavioural specifications and their influence on how buyers evaluate housing outcomes under flood risk.

The final sub-question examines housing market outcomes through simulation experiments and outcome analysis. Model simulations are conducted under different behavioural, flood risk and market condition scenarios. Outputs are analysed to assess changes in housing prices, transactions, and spatial patterns. This allows the identification of how behavioural assumptions influence market dynamics.

Data requirements, data sources and analysis tools

This study builds on the RHEA-NL agent-based housing-market model developed by Mutlu and Filatova (2026). Its inherited empirical inputs comprise NVM housing transactions from Maastricht between 1995 and 2020, historical inundation maps from Rijkswaterstaat, current flood-prone and protected areas from Deltares, and river and city-centre coordinates from OpenStreetMap. These data are used to create a synthetic and anonymised housing stock

of 3,000 properties representing a typical urban region in Limburg rather than a specific area. The collection, preparation and calibration of these spatial and housing-market data are not undertaken in this research. They instead provide the fixed empirical setting within which the behavioural reference-point formulations are developed and evaluated.

The additional data requirements concern the behavioural mechanisms introduced in this study. Parameter values for probability weighting, loss aversion and value-function curvature are derived from prospect theory literature, while the formulations of financial protection and dynamic risk perception draw on empirical studies of compensation expectations and post-flood risk perception. Where the literature does not provide a single value, parameter distributions or alternative scenario levels are used to represent uncertainty and household heterogeneity. The literature therefore provides both the theoretical basis and the behavioural parameters required to operationalise the different reference points.

The main contribution of this research lies in translating these behavioural theories into formal decision rules and implementing the alternative reference-point formulations within the inherited model. This includes adapting household utility calculations, introducing heterogeneous behavioural parameters, constructing the scenario combinations and recording the outcomes required for comparison. Unless a scenario explicitly changes a behavioural or flood-risk assumption, the inherited spatial data, housing stock, household population and market mechanisms remain constant. This controlled design allows differences between scenarios to be attributed to the reference-point formulations rather than to changes in the underlying dataset or market structure.

The model and behavioural extensions are implemented in Python using the Mesa framework (Masad & Kazil, 2015). Simulation outputs are collected across repeated runs and compared using indicators including household utility, bids, transaction prices, transaction frequency and spatial sorting between flood-prone and non-flood-prone areas. These outputs constitute model-generated data rather than new empirical observations. The analysis therefore focuses on relative differences and recurring patterns across scenarios. Its conclusions remain conditional on the inherited data, model structure and behavioural assumptions, which limits their interpretation as precise forecasts of the Limburg housing market.

The research is limited by uncertainty in flood risk projections and evidence on how households respond to flood risk when making housing decisions. Historical data and observed behaviour may also not accurately represent current beliefs or how households will respond to changing risks in the future. Simplifying complex household preferences and market interactions into formal decision rules may exclude factors that influence real housing choices. These limitations are addressed by grounding behavioural assumptions in existing literature, comparing alternative scenarios and evaluating whether the model reproduces plausible housing market patterns. The results are therefore interpreted primarily as relative differences between behavioural formulations rather than precise predictions.

Stakeholder analysis

The study concerns stakeholders who influence, participate in or are affected by housing market decisions under flood risk in the Limburg river area. Their relevance differs according to their role in the local housing market and their ability to influence the market, flood risk management or financial protection. Although the stakeholders shown in Table 2 are not all represented in the model, their decisions and institutional roles determine the context represented by the scenarios.

Table 2. Stakeholder analysis of the housing market under flood risk in Limburg

Stakeholder	Interest	Influence	Relevance to the study
Households	High	Low	Households are the principal actors represented in the model. Their income, risk perception and housing decisions influence property evaluations, bids, asking prices and residential location choices.
Municipalities & Province Limburg	High	High	Local and regional authorities influence spatial planning, housing development and flood risk communication. The results can help them understand how behavioural responses may affect property prices, market activity and the distribution of vulnerable inhabitants.
National government	High	High	The national government determines important aspects of flood risk policy and financial compensation. Expectations concerning public compensation and flood protection influence households' risk evaluation.
Waterschap Limburg	High	High	This organisation manages flood protection and communicates risk information. Model outcomes can indicate how changes in objective flood probability and risk communication influence the housing market.
Mortgage lenders and insurers	High	High	Lending conditions, property valuation and insurance conditions affect housing affordability and households' exposure to financial losses. These organisations may use the results to assess how behavioural responses to flood risk influence market and credit risks.
Real estate agents	High	Medium	Realtors connect buyers and sellers and contribute to asking prices and market valuations. They can use the findings to recognise how flood risk and household perceptions are reflected in bids and transaction prices.

Households and real estate professionals have a high interest in the problem but limited individual power to alter the institutional and physical conditions surrounding flood risk. Their influence primarily emerges collectively through housing choices, property valuations and market practices. Government bodies, water authorities and financial institutions possess greater direct influence because they can change spatial planning, flood protection, compensation arrangements, lending conditions and financial protection. These stakeholder roles provide the societal and institutional context within which the model results are interpreted. The following sections translate this context into the behavioural model by explaining the implementation of prospect theory, the selected reference points and the experimental scenarios.

Prospect theory & reference point implementation

Household decisions in flood-prone housing markets involve uncertain outcomes with low-probability but high-impact events. Standard expected utility models assume evaluation over final wealth and linear probabilities and expectations. This, however, might not adequately capture decision making under such circumstances.

This study therefore adopts the cumulative prospect theory (CPT) framework by Tversky and Kahneman (1992), where households evaluate outcomes as gains and losses relative to a reference point. The framework allows for loss aversion and probability weighting, meaning that households place more importance on potential losses and tend to overestimate the likelihood of rare events. This makes it well suited to modelling risks such as flooding, where low-probability but high-impact outcomes play an important role. This section outlines the parameters, specifies the value functions for gains and losses, and describes the alternative reference points used to calculate household utility within the extended agent-based model.

To start, for the calculation of utility in all reference points the following probability weighting function is adopted as described by Tversky and Kahneman (1992).

$$\Omega(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}} \quad (1)$$

In case of a probability concerning positive effects Tversky and Kahneman (1992) find a value of 0.61 for γ , and 0.69 in case of losses. These findings are reaffirmed by Bernheim and Sprenger (2019) and Abdellaoui (2000). This probability weighting function describes how individuals perceive and transform objective probabilities. Figure 2 shows these weighting functions for both gains and losses and visualises how people often overweight small probabilities and underweight larger ones, with the objective probability on the diagonal.

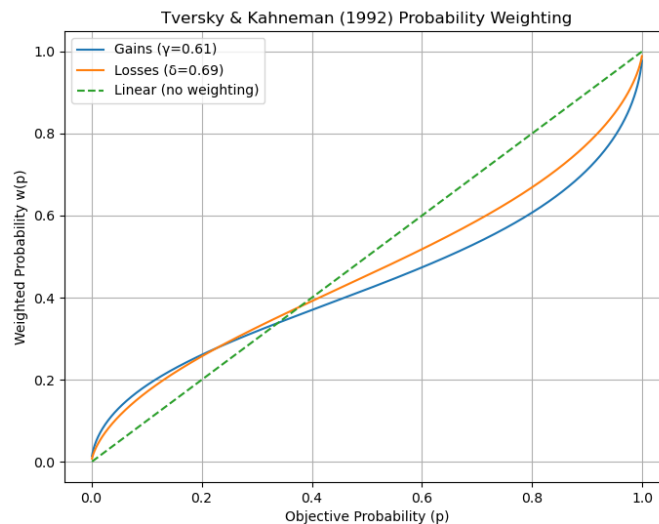


Figure 2. Real(diagonal) and perceived probability under prospect theory

Rieger et al. (2017), however, showcase that these probability weighting functions also vary substantially between countries and regions. To stay close to the Dutch situation, probability weighting values that correspond to the Netherlands are also applied in the model. They find values for γ of 0.82 for positive effects and 0.73 for events that are considered losses. These values, for both gains and losses, are higher than earlier estimates, indicating that probability skewing effect is weaker in the Netherlands. Additionally, to introduce heterogeneity a standard deviation is set at 0.025 in similar fashion to Haer et al. (2017).

Another core component of prospect theory is loss aversion. Loss aversion refers to the tendency for individuals to experience losses more strongly than gains of an equal size. In other words, the negative utility associated with a loss is generally greater than the positive utility associated with an equivalent gain. This implies that households are likely to place greater weight on potential flood related losses than on comparable gains in property value, leading to more risk averse behaviour under uncertainty.

The parameter (λ) of loss aversion was originally found by Tversky and Kahneman (1992) to be 2.25 on average. This value was however based on a small group of participants choosing between relatively low impact outcomes (He & Zhou, 2010). The loss aversion parameter has since been widely studied. Rieger et al. (2017) find an average loss aversion parameter value in the Netherlands of 1.47, which was also adopted in the model. Brown et al. (2022) performed a comparative study of 607 different loss aversion estimations. They find the average loss aversion coefficient to be 1.955 with a 95% probability that the true value falls in the interval [1.820, 2.105]. Therefore, a loss aversion parameter standard deviation of 0.0765 is applied to introduce more heterogeneity to the model.

Tversky and Kahneman then formulate the following value function, $v(x)$ using these values.

$$v(x) = \begin{cases} x^\alpha, & x \geq 0 \\ -\lambda(-x)^\beta, & x < 0 \end{cases} \quad (2)$$

They define different utility functions depending on whether the outcome (x) is positive or negative relative to a reference point. Finally, they find average curvature parameters of 0.88 for both gains (α) and losses (β), indicating a diminishing sensitivity to increasing gains or losses. This value, however, sees varying estimates in recent literature. Brzezicka and Tomal (2023), show that for housing specifically the value for α is around 0.75 on average and β at 0.53. More generally, they point to the findings of Rieger et al. (2017) that show values between 0 and 1 for both gains and losses across 50 of 52 countries which is also reaffirmed by Abdellaoui (2000) who found values very close to Kahneman's initial estimates. For this research Kahneman's value (0.88) is used for both gains and losses.

Reference points

The final key element of prospect theory is the reference point. Reference points are baseline outcomes against which people compare other states or outcomes (Kahneman & Tversky, 1979). The point where we set this reference point therefore strongly dictates whether something is considered a gain or a loss. However, it remains unclear where people set this reference point when faced with housing decisions under flood risk. In the literature, reference points such as initial wealth, no flood expectation and wealth before ownership have already been tested (Haer et al., 2017; De Koning et al., 2017).

In this research multiple reference points and their utility functions are described. Consecutively, they have been implemented into a housing market model and their effects on housing market outcomes in river areas under flood risk have been observed.

Inherited Baseline

In the inherited expected utility baseline (Mutlu & Filatova, 2026), the annual objective flood probability (p) is converted into the probability of at least one flood occurring during household (i)'s expected residence period (RT_i) as shown in Equation 3. This probability is used in Equation 4 to calculate the expected flood losses during the residence time by multiplying it with the property market value P_j and the fixed flood damage ratio L . The flood damage ratio is set at 0.17 following the findings of Endendijk et al. (2023).

$$p_{base,i} = 1 - (1 - p)^{RT_i} \quad (3)$$

$$E[L_{ij}]_{base} = p_{base,i} * P_j * L \quad (4)$$

$$Utility_{base} = P_j - E[L_{ij}] - LT_j \quad (5)$$

Equation 5 subtracts the expected flood loss from the property market value and deducts the listing-time discount (LT_j) that is applied to properties on the market that remain unsold for a while. This objective risk formulation serves as the inherited benchmark, while the subsequent prospect theory formulations fundamentally restructure how households evaluate flood outcomes through reference dependence, loss aversion and subjective probability weighting.

PTNull

The first introduced reference point closely follows PTNull by de Koning et al. (2017). Households use the current market value under a no-flood outcome as their reference point and evaluate flood-related losses relative to this benchmark. The general utility structure remains comparable to the baseline, while the expected flood-loss calculation is replaced by prospect theory-based evaluation:

$$Utility_{PTNull} = (P_j - E[L_{ij}])^\beta - LT_j \quad (6)$$

Expected losses are calculated using two formulations. First, PTNullS represents the expected loss as a single probability-weighted outcome as shown in Equation 7. Here, $\Omega(p)$

denotes the subjective weighting of the objective annual flood probability according to CPT as described earlier and λ_i represents the household-specific loss-aversion coefficient:

$$E[L_{ij}]_{NULLS} = (\Omega(p) * RT_i * L * P_j) * \lambda_i \quad (7)$$

This simplified formulation applies the weighted expected loss directly and therefore does not distinguish between zero, one or multiple floods during the residence period. PTNullC addresses this limitation by evaluating the probabilities and perceived losses associated with separate flood-event outcomes.

$$Utility_{PTNullC} = \left(P_j - \sum_{N=1}^4 (p_N * E[L_N]) \right)^\beta - LT_j \quad (8)$$

$$E[L_N] = P_j * N * L * \lambda_i \quad (9)$$

$$p_N = \frac{RT_i!}{N! (RT_i - N)!} * \Omega(p)^N * (1 - \Omega(p))^{RT_i - N} \quad (10)$$

The model considers flood event outcomes from zero to four floods during the residency period, while the probability of five or more floods is treated as negligible and its impact on utility calculation would therefore be very low, while increasing computational complexity. The objective flood probability is first transformed into a subjective annual probability using the probability weighting functions described earlier. The subjective annual flood probability is then used to calculate the subjective probability of N number of floods happening (p_N) throughout the expected residency time using a binomial distribution. For each N number of floods, the expected losses are multiplied by their accompanying subjective probabilities.

Insurance and financial protection

An additional reference point can be introduced through perceived insurance and compensation mechanisms. Buyers may assume that part of their potential flood losses will be compensated through private insurance, the Dutch Calamities and Compensation Act (CCA), or disaster relief funds, which affects how losses are perceived and valued (Botzen & van den Bergh, 2012). Evidence from the 2021 Limburg floods shows that households expected to receive compensation for approximately 60% of total flood damages on average through a combination of homeowner insurance, home contents insurance, disaster funds, and public compensation schemes (Endendijk et al., 2023). This can be operationalised by multiplying expected flood losses by an expected compensation rate that varies across scenarios, representing different levels of perceived financial protection.

Flooding from regional waterways and extreme rainfall is often covered through homeowner and home contents insurance policies, while large scale river or dike failure flooding may fall under government compensation schemes such as the Dutch Calamities and Compensation Act. As a result, compensation outcomes remain uncertain and dependent on both the type of flooding and the institutional response following a disaster.

Even though a large proportion of damages is covered, households still expected around 40% of damages to remain uncompensated several months after the event. As a result, households may form subjective reference points based on partially compensated rather than fully insured outcomes, which can substantially influence loss aversion and flood risk evaluation under prospect theory. This reference point uses the utility and flood losses functions of PTNullC as a base, except flood losses are now multiplied by a perceived uncovered damages factor (u). Values of u range between 0.20 and 0.60 depending on scenario and flood damages are calculated using equation 11.

$$E_{FP}[L_N] = P_j * N * L * u * \lambda_i \quad (11)$$

Expected market value

The forward expected market value reference point assumes that buyers evaluate a property relative to its expected no flood future value. This benchmark is based on the current estimated market price, adjusted by expected market appreciation over the residency period. Flood damage is then perceived as a loss relative to this expected future no flood outcome, meaning that riskier properties are evaluated not only by direct damage, but also by the loss of expected future value. The subjective probability of N floods occurring (p_N) remains the same as in the PTNullC scenario (Equation 10).

The utility calculations for this reference point can be found in equations 12 through 14. Here, the objective housing price is replaced by the expected property value, which is the property's current market value cumulatively growing at the average rate of return in the Dutch housing market. A yearly housing market return of 5% is used based on historical Dutch housing price developments between 1995 and 2025 reported by the central bureau of statistics Netherlands (CBS, 2026). Data on existing owner occupied dwellings in this timeframe show an average annual price increase of approximately 5.7%, making a 5% expected annual return a conservative long term estimate for forward looking household expectations.

$$EPV_{i,j} = P_j * ((1 + r)^{RT_i}) \quad (12)$$

$$Utility_{PT_{EMV}} = \left(EPV_j - \sum_{N=1}^4 (p_N * E[L_N]) \right)^\beta - LT_j \quad (13)$$

$$E[L_N] = EPV_j * N * L * \lambda_i \quad (14)$$

Dynamic risk perception

To represent the effects of flood risk myopia and amnesia introduced in the literature review, perceived flood risk is allowed to vary across households following flood experiences. Recent flood experience temporarily increases perceived flood probabilities, while prolonged periods without flooding gradually reduce perceived risk through behavioural forgetting (Gallagher, 2014; Bubeck et al., 2020). These dynamics are implemented using a temporary

perception shock parameter and a memory decay parameter inspired by Viglione et al. (2014, eq. 3d), without introducing new flood events throughout the simulation.

$$p_t = p_0 * e^{-\delta t_{fe,i}} \quad (15)$$

$$p_0 = p_{obj} + p_{shock} \quad (16)$$

Here delta (δ) represents the time decay parameter, p_{shock} the initial increase in risk perception directly after a flood and p_{obj} the objective flood risk. Gallagher (2014) shows that flood insurance uptake increases sharply immediately after flood events (nearly doubled) and then gradually declines over approximately nine years. This supports the use of a temporary perception shock parameter p_{shock} representing a doubling of objective flood probability immediately after flooding. The gradual decline observed by Gallagher (2014) and Bubeck et al. (2020) supports a memory decay parameter (δ) in a range between 0.15 and 0.25. Therefore, to introduce some heterogeneity, households are assigned a decay parameter value from a normal distribution with average value 0.20 and a standard deviation of 0.0255.

To support this reference point, households now gain a new property that tracks their last flood experience in years $t_{fe,i}$. During the creation of a household within the model every household is uniformly assigned a value for $t_{fe,i}$ between 0 and 12 years depending on scenario. Using the new dynamic risk perception, the utility function remains the same as PTNull, but the risk probabilities become:

$$Utility_{PTDynamic} = \left(P_j - \sum_{N=1}^4 (p_N * E[L_N]) \right)^{\beta} - LT_j \quad (17)$$

$$p_N = \frac{RT_i!}{N! (RT_i - N)!} * \Omega(p_t)^N * (1 - \Omega(p_t))^{RT_i - N} \quad (18)$$

Further model extensions and adaptations

Climate change and flood probability

Climate change affects the world in many more ways than just global warming. One of these pathways will be through more extreme weather events and more frequent inland flooding with increasing damages (IPCC, 2023). Climate change and global warming could double flood probability across 40% of the globe and over 60% in certain parts of the world in 2050 relative to a scenario where no further climate change would occur (Arnell & Gosling, 2014).

In later research Arnell et al. (2019) test river flood probability against multiple increases of global temperature compared to pre-industrial times. They estimate that at a 1.5 °C increase, which is the current level, flood frequency of 1-in-50-year floods increases to 2.4% annually and 1-in-30-year floods increase to 4.4% annually. At an increase of 2 °C, these probabilities rise to 2.9% for 1-in-50-year floods and 5.3% for 1-in-30-year floods. In an extreme case with 4 °C of global warming these probabilities grow to 5.4% for 1-in-50-year floods and 10.3% for 1-in-30-year floods. Therefore two increased climate risk scenarios are

introduced to reflect further human-induced global warming. First, a scenario with mild further temperature increases where objective flood probability increases from 2% in the base model to 3% annually without protection measures in place. Secondly, an extreme global warming scenario where objective probability increases to 5% without protection.

Bid price scaling and calculation

The behavioural utility formulations described above determine how households evaluate available properties, but do not directly specify the monetary offers submitted within the housing market. A separate bidding mechanism is therefore required to translate the resulting property rankings into bid prices. In the original model, this mechanism considers up to five properties, ranks them according to household utility and derives the associated bids primarily from flood risk discounted expected utility. A household-specific price margin parameter ($H_{f,i}$) that is uniformly assigned between -5% and $+5\%$ spaces offers across the ranked properties, while zero produces no additional adjustment (Mutlu & Filatova, 2026). Since objective flood losses already reduce utility, most of the bid discount occurs before this parameter is applied.

In the present study, the prospect theory calculations produce substantially lower utility values because flood outcomes are evaluated with subjective probability weighting and perceived losses are amplified through loss aversion. Directly translating these values into monetary bids produces unrealistically low offers and repeated transaction failures, preventing the housing market from functioning. A new mapping is therefore required to retain realistic bid levels while preserving the strong influence of utility. The revised formulation uses the asking price as a monetary anchor and applies a property-specific factor determined by the utility gap and overall choice-set quality. The original household-specific bidding behaviour and listing time are subsequently incorporated into the final bid price.

Calibrating a housing market model such that households bid slightly below their estimated valuation for less preferred properties and closer to their full valuation for their most preferred properties is consistent with empirical evidence on heterogeneous willingness to pay (WTP). Buyers exhibit substantial variation in their valuation of housing attributes, even among otherwise comparable properties.

Empirical evidence further suggests that highly attractive properties can command price premiums due to competition among buyers. For example, Chow et al. (2015) find that auctioned apartments in Singapore sold on average approximately 7% above comparable negotiated sales, while Thanos and White (2014) report substantial overbidding in the Scottish sealed bid system during strong market conditions. In addition, studies on environmental and residential amenities demonstrate that households assign markedly different values to preferred property characteristics, leading to considerable variation in WTP across a given set of housing alternatives (Jensen et al., 2021; Caplan et al., 2021).

Together, this evidence supports modelling bids as moderate deviations around estimated market valuations reflecting household-specific preferences. Rather than using a fixed bidding range, the present model determines the property-specific bidding factor ($U_{f,ij}$)

based on two characteristics of the household's considered choice set. First, choice set quality compares the utility of the highest ranked property with the maximum attainable utility within the household's affordable search space (Equation 20). This prevents households from automatically bidding their full valuation when only relatively unattractive properties are available.

Second, the utility gap between the highest and lowest ranked properties determines the width of the bidding range (Equation 19). Larger differences in utility result in greater variation in bids, whereas similar properties produce more comparable bid prices. Consequently, households submit bids closer to their full valuation for highly preferred properties within attractive choice sets while applying larger discounts to less desirable alternatives or when only low utility properties are available.

$$U_{min,i} = 0.90 - 0.10 * \left(\frac{U_{max,j} - U_{min,j}}{U_{max,j}} \right) \quad (19)$$

$$U_{max,i} = 0.95 + 0.05 * \left(\frac{U_{max,j}}{U_{max,budget}} \right) \quad (20)$$

$$U_{f,ij} = U_{min,i} + U_{norm,ij} * (U_{max,i} - U_{min,i}) \quad (21)$$

Additional heterogeneity is introduced through the inherited household-specific price margin parameter ($H_{f,i}$) from Mutlu & Filatova (2026), which captures differences in bidding behaviour between households. This parameter allows some households to bid more aggressively or conservatively across all properties, resulting in occasional overbidding even when the property-specific utility factor remains below the asking price ($P_{ask,j}$). The final bid formulation (Equation 22) also incorporates listing time discounts (LT_j), allowing both property characteristics and household behaviour to influence transaction prices.

$$\text{Bid Price}_{ij} = P_{ask,j} \cdot U_{f,ij} \cdot H_{f,i} \cdot (1 - LT_j) \quad (22)$$

The listing time discount calculation remains unchanged from Mutlu and Filatova (2026), but is now also incorporated into the bidding price calculations. This allows households to also adjust their bids in response to the time a property has been listed on the market, reflecting the tendency of buyers to negotiate more aggressively for properties that have remained unsold for extended periods. Consequently, listing time influences both household preferences and the final transaction price formation process. Calculation of listing time discount is property specific and performed as follows:

$$LT_j = \min(0.15, \tau \ln(1 + s_j)) \quad (23)$$

Here, τ is a parameter that determines the strength of listing time discounts and s_j tracks the amount of time that a property has remained unsold.

Overview of model action sequence and adaptations

Figure 3 illustrates the sequence of activities performed during a single model time step. At the beginning of each step, the realtor and households are initialised, with the latter receiving the prospect theory parameters introduced in this study. The realtor first estimates market values based on recent transaction data, after which sellers determine asking prices using these estimates. These pricing mechanisms are inherited from the original housing market model of Mutlu and Filatova (2026).

The principal contributions of the present study occur during the household decision-making process. Buyers search for affordable properties and evaluate them using the implemented behavioural framework, which incorporates prospect theory based utility calculations and flood risk perception. This calculated utility is subsequently translated into bid prices through the newly developed bidding mechanism. Sellers then evaluate the received bids against their reservation price. Successful bids result in property transactions and corresponding updates to household and property states, whereas unsuccessful negotiations trigger updates to buyers' bidding behaviour and sellers' pricing strategies before the next simulation step begins.

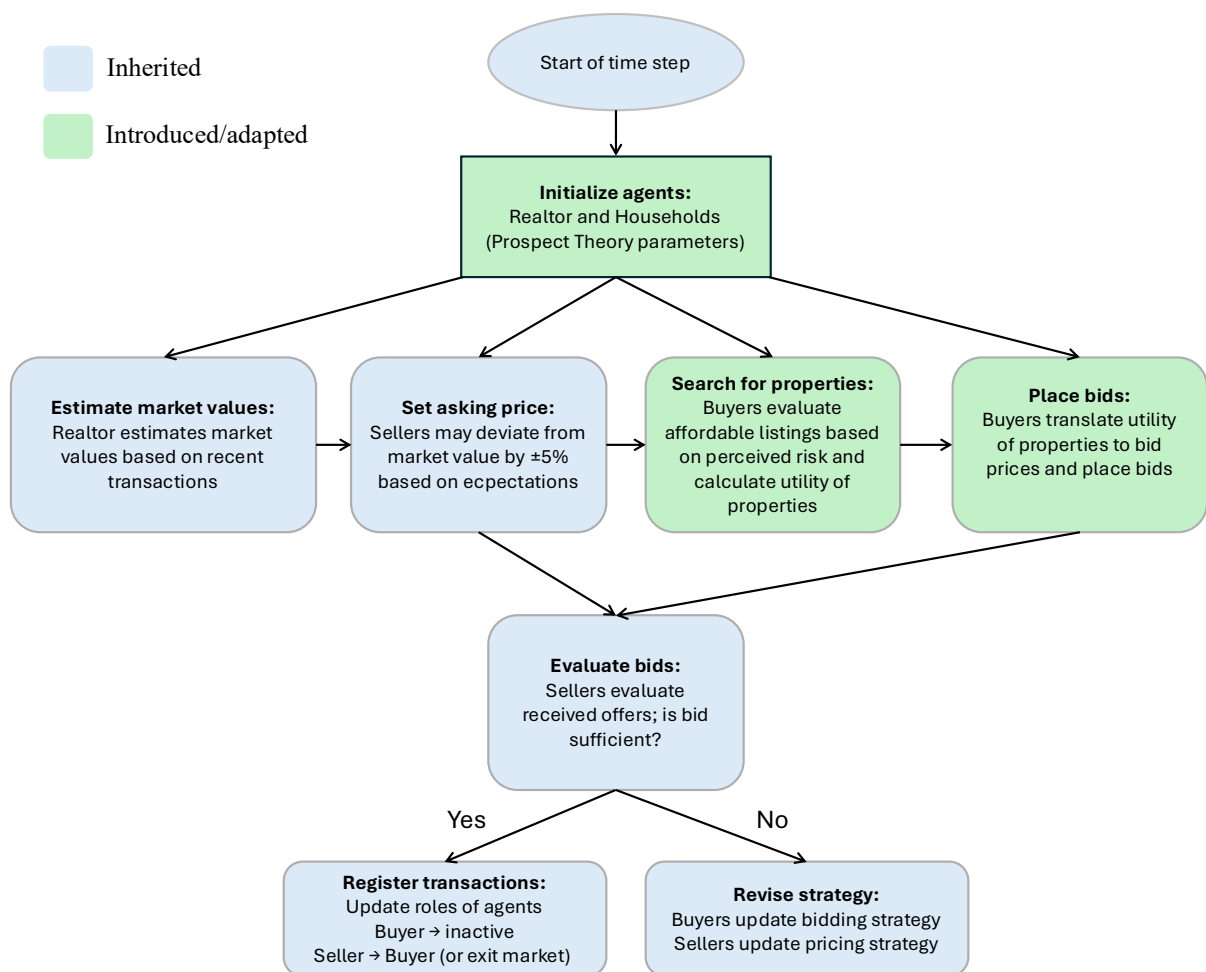


Figure 3. Adapted sequence of actions in the agent-based housing market model

Model structure and behavioural extensions

Figure 3 illustrates the sequence of actions through which housing-market interactions unfold during each model step. To complement this process perspective, Figure 4 presents a class diagram showing the model's principal components and their relationships. Green elements indicate components introduced or substantially modified in this study, while the remaining elements represent the inherited RHEA-NL model structure.

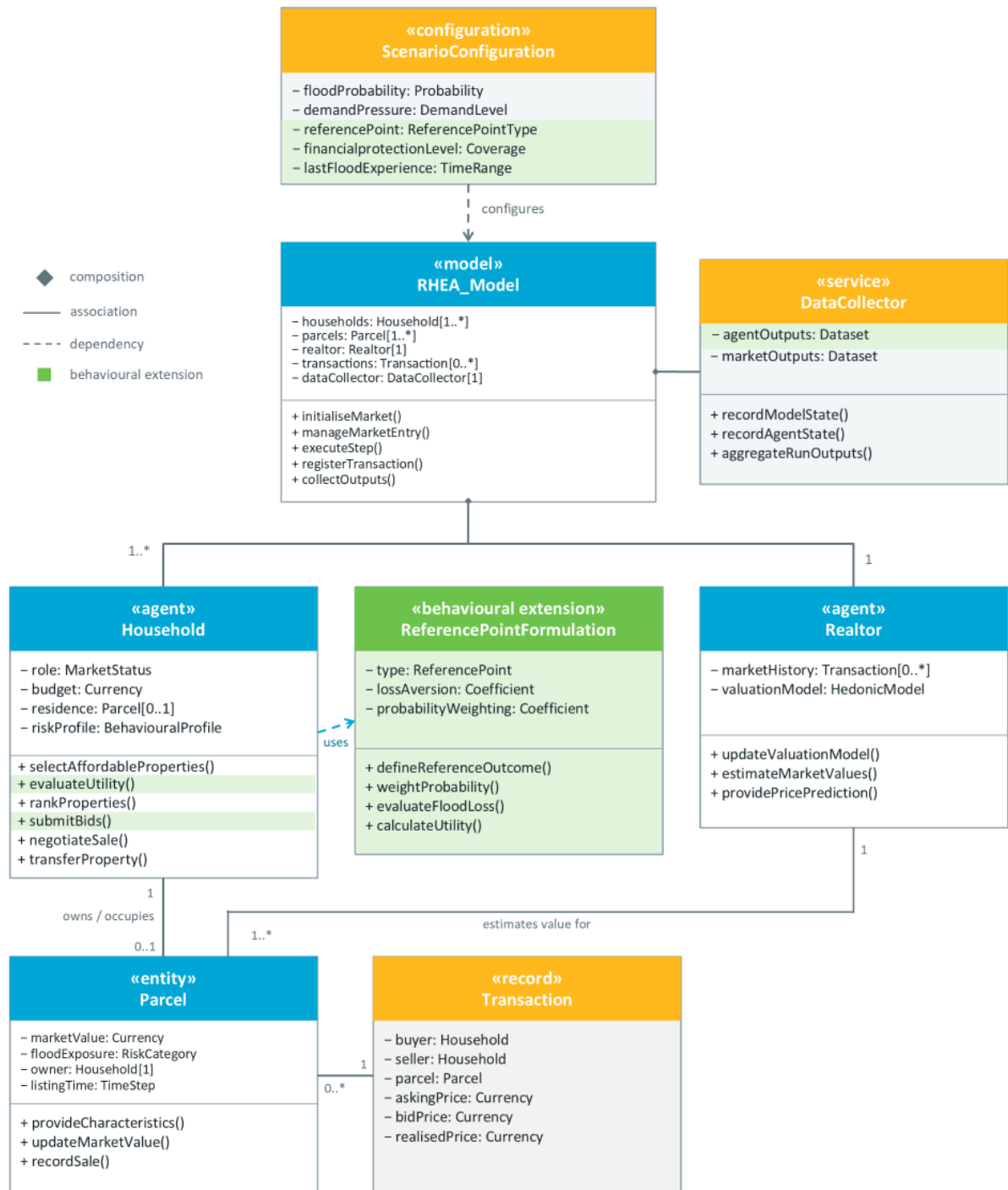


Figure 4. Class diagram of the RHEA-NL housing-market model and the prospect theory extensions introduced in this study. Green elements indicate components introduced or substantially modified in this research.

At the centre of the model, the central model class coordinates the housing market and maintains the collections of households, parcels and completed transactions. It also manages the realtor and data collector. The scenario configuration supplies the assumptions selected for each simulation before the model is initialised, but does not participate as an active agent. The central model subsequently coordinates agent activation and ensures that market information, ownership changes and transaction records remain consistent throughout the simulation.

Households form the principal decision-making agents. Each household can own a maximum of one parcel and may participate in the market as a buyer or seller. Buyers identify affordable properties, evaluate and rank them, and submit bids. Sellers assess received bids and transfer ownership following a successful transaction. Parcels are passive entities that contain the physical, spatial and flood-exposure characteristics of properties, together with their changing ownership, listing and market information. The realtor is the second agent type and estimates property market values using a hedonic valuation model and available transaction history. This separates market-level price estimation from the heterogeneous preferences and decisions of individual households.

The main behavioural extension operates within household property evaluation. The reference point formulation shown in Figure 4 represents the decision logic implemented within the household rather than an independently activated agent. It combines the definition of a reference outcome with subjective probability weighting, loss aversion and utility calculation. Alternative formulations change the benchmark against which potential flood outcomes are evaluated while retaining a consistent surrounding market structure.

The conversion of utility into monetary bids is also substantially modified. Directly applying the prospect theory utility values to bids produces unrealistically low offers because perceived flood losses strongly reduce the absolute utility scale. The revised procedure therefore uses relative utility to position bids around the property price while preserving the influence of household preferences and bidding aggressiveness. This allows behavioural differences to affect bidding without preventing market transactions.

Following an accepted bid, a transaction record connects the buyer, seller and parcel with the associated asking, bid and realised prices. Ownership is then transferred directly between households. The data collector records both model-level and agent-level information. In this study, the existing agent reporters are extended to retain households' bid records, loss-aversion values and probability-weighting values for subsequent analysis. Green elements in Figure 4 identify components introduced or substantially modified in this study, while the remaining elements represent the inherited RHEA-NL model structure. The following sections describe the model parameters, experimental scenarios and recorded output variables in greater detail.

Parameter table

The behavioural housing-market model contains a range of parameters adopted from the original model of Mutlu and Filatova (2026), alongside additional parameters introduced or modified to represent prospect theory and the reference points described earlier. Table 3

provides an overview of the main model parameters, their values or distributions, and the sources used to justify their selection. Where parameters vary between scenarios, the corresponding values or distributions are reported together. Blue shading identifies parameters inherited from the original model, while green shading indicates parameters introduced or modified in this study.

Table 3. Parameter and value overview, inherited parameters in blue and new parameters in green

Symbol	Description	Value/distr.	Source
Global parameters			
p_{obj}	Scenario specific objective annual flood risk in flood-prone areas	2%, 3%, 5% (scenarios)	IPCC (2023) Arnell et al. (2019)
L	Flood damage ratio	=0.17	Endendijk et al. (2023)
τ	Listing-time price discount strength	=0.02	Model design
T, k_Y	Simulation duration and number of time steps per year	30 years; 2 steps/year	Model design
D	Housing-demand pressure, ratio of buyers to sellers	1; 2 (medium; high)	Scenario design
n_{view}, n_{bid}	Properties sampled and maximum properties selected for bidding	10; 5	Model design
α, β	Sensitivity parameter to larger values of gains and losses	=0.88	Tversky & Kahneman (1992)
u	Perceived uninsured damages parameter	=0.20, 0.40, 0.60 (PTFP1, 2, 3)	Endendijk et al. (2023)
r	Expected annual rate of return on housing	=0.05	CBS (2026)
p_{shock}	Increase in subjective flood risk perception after flood experience	=1 * p_{obj}	Gallagher (2014)
Household parameters (household index: i)			
RT_i	Intended residence time	Normal dist. ($\mu=17, \sigma=1.5$)	Wigt et al. (2012)
$H_{f,i}$	Household-specific price margin	Uniform dist. [-5,5]%	Model design
γ	Prospect theory probability weighting parameter for gains and losses	Normal dist. ($\mu=0.82$ gain; $\mu=0.73$ loss; $\sigma=0.025$)	Rieger et al. (2017) Haer et al. (2017)
λ_i	Loss aversion coefficient	Normal dist. ($\mu=1.47, \sigma=0.0765$)	Brown et al. (2022) Rieger et al. (2017)
δ_i	Subjective flood risk time decay parameter	Normal dist. ($\mu=0.20, \sigma=0.0255$)	Gallagher (2014) Bubeck et al. (2020)
$t_{fe,i}$	Time since last flood experience	Uniform dist. [0,4],[4,8],[8,12] (PTDR1, 2, 3)	Model outcome & start condition
Property parameters (property index: j)			
s_j	Number of time steps unsold	Endogenous variable	Model outcome
LT_j	Listing time price discount (logarithmic capped at 0.15)	= $\min\{0.15, \tau \ln(1 + s_j)\}$	Model design

Scenario design

The purpose of the scenario design is to systematically evaluate how different prospect theory reference points influence housing market behaviour under varying levels of flood risk. A baseline scenario without prospect theory is first established and compared against five alternative reference point formulations: PTNullS, PTNullC, expected market value, financial protection, and dynamic risk perception. Each reference point is evaluated under objective annual flood probabilities of 2%, 3%, and 5%, representing current and future climate conditions.

Additional sub-scenarios are introduced for the financial protection and dynamic risk perception reference points by varying levels of perceived financial compensation and flood experience recency respectively. Together, these scenarios allow for the assessment of how alternative behavioural assumptions influence household utility, bidding behaviour, property values, and broader housing market dynamics under increasing flood risk.

Table 4. Scenarios and utilised reference points

Scenario	Reference point	Description	Demand	Flood probability
Base	None	Expected utility	1;2	2;3;5%
PTNullS	PTNullS	Single expected flood loss	1;2	2;3;5%
PTNullC	PTNullC	Event-based flood losses	1;2	2;3;5%
PTEMV	Expected market value	Value appreciation assumed	1;2	2;3;5%
PTFP 1-3	Financial protection	Compensation adjusted loss evaluation, at low, moderate, high compensation levels	1;2	2;3;5%
PTDR 1-3	Dynamic risk	Time sensitive risk perception at recent, moderate and distant flood experiences	1;2	2;3;5%

Each reference point is evaluated under annual flood probabilities of 2%, 3%, and 5%. Housing demand pressure is set at medium (1) and high (2) in all scenarios, indicating the relative number of buyers to sellers in the market. This is done to reflect the Dutch housing market and ensure that subsequent policy recommendations are grounded in a realistic market context. The financial protection and dynamic risk perception reference points are further subdivided into three additional levels, resulting in a total of 60 scenario combinations. Unless otherwise specified, all model components remain unchanged between scenarios, allowing observed differences in outcomes to be attributed to the respective reference point formulations.

A consistent set of indicators is required to assess how these scenario variations affect household decisions and housing-market dynamics. The following section therefore describes the output variables tracked to evaluate and compare the simulation results. With this analytical basis established, the subsequent sections specify the individual scenarios and explain their respective purposes within the experimental design.

Output variables and trackers

To evaluate the effects of the different prospect theory reference points, a set of housing market indicators is recorded throughout each simulation. These indicators capture transaction prices, bidding behaviour, market activity and the utility associated with submitted bids. Unless stated otherwise, the outputs are reported separately for properties located within and outside the flood zone, enabling direct comparison of market outcomes across both areas. The relative flood-price discount is subsequently derived from the average transaction prices in both zones.

Table 5. Tracked data for analysis

Output parameter	Unit	Description
Average transaction price	€	Mean realised transaction price
Relative flood-price discount	%	Difference between non-flood-prone and flood-prone properties
Average bid price	€	Mean bid submitted by households
Number of bids placed	Count	Mean number of bids submitted
Number of transactions	Count	Total completed property transactions
Transaction fraction	%	Share of available properties that are sold
Average utility	Utility	Mean utility associated with bids submitted
Household income	€ year ⁻¹	Annual income of households
Loss aversion strength	#	Household loss aversion parameter value
Probability weighting strength	#	Household probability weighting value

The relative flood-price discount is calculated from the average transaction prices in the two zones as follows:

$$Discount (\%) = \frac{Price_{non\ flood} - Price_{flood\ prone}}{Price_{nonflood}} \times 100 \quad (24)$$

The calculation is applied separately to each reference-point formulation, flood probability and housing-demand condition after final-year transaction prices are aggregated across the Monte Carlo runs. A positive value indicates a discount for flood-prone properties, a value of zero indicates no price difference, and a negative value indicates a price premium.

Household income, loss aversion and probability weighting are retained as agent attributes and linked to households' final residential locations. This enables the analysis of spatial sorting by examining whether households with different economic and behavioural characteristics become concentrated within or outside the flood zone. More broadly, each group of outputs addresses a specific component of the research questions. Average utility and bid prices capture how alternative reference points affect individual housing evaluations and bidding decisions.

Transaction prices, flood-price discounts and transaction fractions show how these decisions translate into aggregate market activity and the capitalisation of flood risk. Household attributes and final locations reveal the resulting distribution of flood exposure. Together, the indicators shown in Table 5 allow the reference-point formulations to be compared across flood probabilities and housing-demand conditions, supporting the assessment of their effects on individual decisions, market outcomes and spatial sorting.

Purpose and specification of scenarios

Base scenario

The baseline scenario represents the Dutch housing market under current market conditions and serves as a benchmark for all prospect theory scenarios. Household utility is calculated using an expected utility framework with objective flood risk perception, meaning that households evaluate flood probabilities directly without probability weighting, loss aversion or reference points. Consequently, bids in the baseline scenario are derived from expected utility using the same calibrated bidding mechanism applied in the prospect theory scenarios, ensuring that scenario differences are attributable to the utility framework.

Medium and high housing demand pressure are included in this and all other scenarios to more closely reflect the Dutch housing market. This is done to ensure that subsequent policy recommendations are grounded in a realistic market environment. Each simulation covers a 30 year period, divided into two time steps per year, resulting in 60 model steps per simulation. This duration allows both short term behavioural responses and longer term housing market effects to emerge. To account for stochastic variation, each scenario is simulated 50 times using Monte Carlo runs. The same simulation length, time step structure and number of runs are applied to all scenarios to ensure comparability.

PTNullS

The PTNullS scenario introduces prospect theory into the housing market model through a simplified reference point formulation. Household utility is calculated relative to a no flood reference state, while flood risk is represented by a single expected flood loss value. As a result, households exhibit probability weighting and loss aversion, but do not explicitly evaluate individual flood event outcomes.

The purpose of this scenario is to establish a simplified prospect theory benchmark and assess the impact of introducing behavioural decision making relative to the baseline scenario. In addition, PTNullS provides a basis for comparison with PTNullC, allowing the importance of modelling separate flood event outcomes to be evaluated.

PTNullC

The PTNullC scenario extends PTNullS by explicitly evaluating individual flood event outcomes rather than a single expected flood loss value. Household utility is calculated relative to a no flood reference state, with probability weighting and loss aversion applied separately to each flood outcome and its associated probability.

The purpose of this scenario is to assess whether a more detailed representation of flood risk influences housing market behaviour and outcomes. As the primary prospect theory benchmark used throughout this study, PTNullC serves as the reference point against which the alternative prospect theory formulations are compared.

PTMV Expected market value

The expected market value scenario introduces a future wealth based reference point in which households evaluate potential flood losses relative to the anticipated future value of a property. Rather than comparing outcomes with the property's current no-flood value, households evaluate them against its expected future no-flood value.

The purpose of this scenario is to examine how investment oriented decision making influences housing market behaviour under flood risk. In particular, it assesses whether anticipated future capital gains reduce the perceived impact of flood risk and alter households' willingness to bid on properties in flood-prone areas.

PTFP Financial protection

The financial protection scenario extends PTNullC by incorporating perceived insurance and compensation mechanisms into the reference point formulation. Household utility is calculated relative to a partially protected outcome, reflecting the expectation that a proportion of potential flood damages will be covered through private insurance, government compensation schemes, or disaster relief funds.

The purpose of this scenario is to assess how perceived financial protection influences the evaluation of flood risk and subsequent housing market behaviour. Three values are used for the uncovered damage parameter (u): 0.20, 0.40, and 0.60, representing high, moderate, and low levels of assumed financial protection respectively. This allows the sensitivity of household decision making to different compensation expectations to be evaluated.

PTDR Dynamic risk perception

The dynamic risk perception scenario extends PTNullC by incorporating flood risk myopia and amnesia through a time-dependent risk perception function. Rather than perceiving flood risk objectively, households adjust their perceived flood probability based on the time elapsed since their most recent flood experience ($t_{fe,i}$). Consequently, households with recent flood experience perceive higher flood risks than households whose flood experience occurred further in the past.

The purpose of this scenario is to assess how flood experience and memory decay influence the evaluation of flood risk and subsequent housing market behaviour. Three sub-scenarios are considered, with newly created households assigned initial ($t_{fe,i}$) values uniformly drawn from the integer ranges [0,4], [4,8], and [8,12] years respectively. These ranges represent recent, moderate and distant flood experience, allowing the effects of flood risk myopia and amnesia on household decision making to be evaluated.

Model evaluation

Before analysing the behavioural scenarios, the developed agent-based model must be systematically evaluated to ensure that it produces reliable and meaningful results. Model evaluation consists of three complementary stages: calibration, verification, and validation. Calibration is used to determine parameter values that reproduce realistic baseline housing market behaviour. Verification subsequently confirms that the implemented behavioural mechanisms, equations, and model processes have been translated correctly into the simulation code. Finally, validation evaluates whether the calibrated model produces plausible household behaviour and housing market dynamics consistent with theoretical expectations and empirical observations. Together, these evaluation stages provide confidence that the model is suitable for analysing the influence of prospect theory on housing market dynamics under varying flood risk scenarios.

Calibration

As the majority of model parameters were either adopted from Mutlu and Filatova (2026), derived from the literature, or intentionally varied as part of the scenario design, calibration was limited to the newly introduced bid price formulation. The objective was to ensure that the revised bidding mechanism generated realistic housing market dynamics while preserving the behavioural differences introduced through prospect theory.

The calibration process initially assumed that households bid the full asking price for every property, which resulted in limited behavioural differentiation despite variation in household utility. A utility based bid scaling factor was therefore introduced and iteratively calibrated using transaction prices, transaction success rates, and overall market stability. To improve the model's sensitivity to lower utility values, the formulation was subsequently extended with a utility gap adjustment and a choice set quality adjustment. Parameter values were refined until the model produced realistic bidding behaviour while maintaining stable housing market dynamics.

Increasing the upper bidding bound beyond 1.00 resulted in frequent overbidding, quickly driving market prices upward and substantially reducing transaction success in later stages of the simulation. Conversely, reducing the minimum bidding factor below 0.90 for all properties led to very low market activity, particularly in flood-prone regions where perceived utility was already lower. The final formulation therefore retained a baseline bidding range of 0.90 to 1.00, while allowing the minimum bidding factor to decrease to 0.80 for choice sets with large utility differences and reducing the maximum bidding factor to 0.95 when the overall quality of the considered choice set was very low. This adaptive formulation increased the model's sensitivity to lower utility values while preventing households from consistently bidding their full valuation when only relatively unattractive properties were available, resulting in more realistic transaction rates and stable housing market dynamics.

Verification

Verification was performed to ensure that the implemented model corresponds to the conceptual model and equations described in the previous sections. This involved checking the implementation of individual model components, testing edge cases, inspecting agent behaviour during simulation runs, and verifying that output variables were correctly recorded and aggregated.

Table 6. Performed verification activities

Activity	Purpose
Utility calculation	Verify that utility and prospect theory calculations are implemented correctly and respond consistently to changes in flood probability and reference points.
Bid price formulation	Verify that bid prices increase with utility, while the utility gap and choice set quality adjustments influence the minimum and maximum bidding factors as intended.
Parameter inspection	Verify that newly introduced variables and intermediate calculations produce realistic values throughout the simulation through inspection of intermediate model outputs.
Extreme conditions	Verify that newly implemented equations produce the expected outputs under boundary and extreme input conditions.
Model dynamics	Verify that the model produces stable housing market dynamics without unintended behaviours under prospect theory.
Output collection	Verify that all output parameters are correctly recorded, linked to the appropriate property and flood zone, and aggregated across timesteps and simulation runs.

The verification activities mentioned in Table 6 were primarily conducted using the PTNullC scenario at high demand and flood probability of 2%, as this scenario contains the complete implementation of the prospect theory framework while excluding additional reference point adjustments. The remaining scenarios build upon the same implementation by modifying only the reference point formulation and associated intermediate variables. Consequently, verification of the utility calculation, bidding mechanism, model dynamics, and output collection in the PTNullC scenario provides confidence in the correctness of the shared model components. Additional verification in the form of parameter inspection was performed for the intermediate variables introduced specifically for the alternative reference point scenarios.

Utility calculation values were inspected throughout the simulation to verify that they remained consistent with the implemented utility formulation. At the start of the simulation, when transactions occur relatively easily and listing time discounts are limited, the average utility closely corresponds to the transformed market value ($P_j^{0.88}$) for non-flood-prone properties. An average market price of approximately €305,000 resulted in an average calculated utility of around 59,500 (Appendix Figure A2), which is consistent with the transformed market value (Figure A1) after accounting for listing time effects.

Flood-prone properties exhibited a lower average utility of approximately 46,500 (Figure A2) for an average market price of €240,000 (Figure A1), reflecting the additional reduction caused by perceived flood losses. To further verify the implementation, a manual calculation was performed for a representative flood-prone property with a market value of €240,000 using the implemented probability weighting, loss aversion, flood damage ratio, and value function parameters. This resulted in an estimated utility of approximately 46,240, closely matching the model output of approximately 46,500. The remaining difference can be attributed to variation in household characteristics and inaccuracies from reading charts. Together, these checks confirm that the implemented utility formulation produces internally consistent and realistic utility values.

Bid price formulation was verified by comparing the evolution of calculated utility (Figure A2), average asking/realtor prices (Figure A1), and average bid prices (Figure A3) throughout the simulation. As intended, higher utility values consistently resulted in higher bid prices, while on average bids remained slightly below asking prices according to the calibrated bidding formulation. Furthermore, successful transactions continued to occur throughout the simulation, confirming that the bidding mechanism maintained an active housing market without unintentionally preventing transactions or causing market collapse (Figure A4). Together, these results demonstrate that the implemented bid price formulation behaves consistently with the conceptual model and calibration objectives.

Parameter inspection involved monitoring newly introduced parameters and intermediate variables throughout model development by examining intermediate outputs during simulation. This verified that calculated values, including utility, perceived flood risk, reference points, choice set quality, utility gaps, bidding factors, and transaction prices, remained within expected ranges and responded logically to changes in model inputs. Intermediate calculations were inspected under different model conditions to confirm that the implemented equations behaved consistently with the conceptual model.

Extreme conditions verification was performed by evaluating two limiting cases of the prospect theory formulation: a scenario without flood risk and a scenario without expected losses. As expected, increasing the flood probability to 5% substantially reduced the calculated utility of flood-prone properties while maintaining similar transaction price dynamics, confirming that the utility formulation is sensitive to changes in objective flood risk (Figures A7 and A8). Conversely, setting the flood probability to zero or setting the loss aversion parameter to 0 caused the utility of flood-prone and non-flood-prone properties to converge, demonstrating that the prospect theory effects are correctly removed from the utility calculation (Figures A5, A6, A9, and A10).

The small differences observed during the initial years can be attributed to the model initialisation, which incorporates two years of historical housing market data prior to the start of the simulation. In all cases, transaction prices continued to evolve smoothly and the housing market remained active, indicating that the implemented behavioural mechanisms operate correctly under extreme parameter values.

Model dynamics were verified by inspecting the evolution of market values, utility, bid prices, transaction prices, and the fraction of properties sold throughout the simulation. Figures A1 to A4 demonstrate that these variables evolve smoothly over time without numerical instability or unintended market collapse. Furthermore, successful transactions continue throughout the simulation, indicating that the implemented behavioural mechanisms maintain stable housing market dynamics.

Output collection was verified by confirming that all reported variables were correctly recorded, linked to the corresponding property and flood zone, and consistently aggregated across timesteps and multiple simulation runs. The figures presented throughout the verification section (Figures A1 to A10) were generated directly from the collected model outputs, providing additional confirmation that the implemented data collection and aggregation procedures function as intended.

Overall, the verification activities demonstrate that the newly implemented model components were correctly integrated and behave consistently with the conceptual model. The verified implementation therefore provides a reliable basis for the subsequent validation and scenario analyses.

Validation

Following verification of the model implementation, validation was performed to assess whether the model produces plausible housing market dynamics and behavioural responses. As the model is intended for exploratory analysis, validation focuses on the consistency of simulated behaviour with theoretical expectations and empirical findings rather than exact agreement with observed housing market outcomes. The following sections evaluate the baseline housing market, household bidding behaviour, and the model's response to flood risk.

Baseline housing market dynamics

The baseline scenario produces stable housing market dynamics throughout the simulation while exhibiting clear differences between flood-prone and non-flood-prone properties. Average transaction prices increase steadily over time (Figure B1), primarily driven by the sustained high demand pressure implemented in the model. This gradual appreciation is consistent with evidence that persistent housing demand combined with supply constraints is a primary driver of rising house prices and declining affordability in advanced economies (Lee et al., 2022).

Despite the overall price appreciation, flood-prone properties consistently transact at lower prices than comparable non-flood-prone properties, resulting in a transaction price discount of approximately 10.5% by the final simulation year (Figure B1). This closely aligns with empirical studies reporting flood risk discounts between approximately 8% and 11%. For example, Bakkensen and Ma (2020) estimate a 6.3% price discount for homes located within high risk flood zones, while Skouralis et al. (2024) report an average discount of 8.1% for flood-exposed properties in England and Shi et al. (2024) find a 10.8% discount for properties located within high risk flood zones in Australia.

A similar pattern is observed in the calculated household utility associated with submitted bids (Figure B2). Flood-prone properties consistently exhibit lower average utility than non-flood-prone properties, with the utility discount varying between approximately 5% and 15% throughout the simulation. Although the magnitude differs, this pattern is also reflected in the observed transaction prices, indicating that lower household utility is successfully translated into lower willingness to pay and ultimately lower market valuations.

Market activity gradually declines as the simulation progresses. Initially, properties in both flood zones are sold at relatively high frequencies, but transaction rates decrease over time, particularly for flood-prone properties (Figure B3). This decline coincides with a substantial reduction in the average number of bids placed on properties (Figure B5). As housing prices increase more rapidly than household incomes under sustained demand pressure, fewer households remain capable of placing competitive bids. Although new buyers continuously enter the market, many quickly leave after finding that the available properties exceed their affordability constraints. Consequently, transactions become increasingly concentrated among higher income households, who are generally able to afford the remaining properties and increasingly favour non-flood-prone locations. These findings are consistent with empirical evidence that flood-prone properties attract less buyer interest, experience lower market liquidity, and therefore remain on the market for longer than comparable non-flood-prone properties (Shi et al., 2024).

The reduction in transaction activity is further reflected in the average time on market, which gradually increases to almost one year by the end of the simulation (Figure B4). Although affordability constraints increasingly limit transactions, the housing market remains active throughout the simulation, with buyers, sellers and successful transactions continuing to occur over the full simulation period (Figure B6). The increasing marketing time observed in the model is consistent with Shi et al. (2024), who report that properties located in high flood risk areas require significantly longer to sell because of reduced buyer demand and liquidity constraints.

Household behavioural responses

The behavioural responses produced by the prospect theory scenarios are consistent with both behavioural decision theory and empirical evidence on flood risk perception in housing markets. Across all scenarios, lower subjective utility of flood-prone properties translates into lower willingness to pay, lower transaction prices and reduced transaction activity, demonstrating that behavioural changes propagate consistently from household preferences to aggregate market outcomes. This is consistent with prospect theory, which proposes that decisions under risk are influenced by nonlinear probability weighting, reference dependence and loss aversion rather than objective expected utility (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992).

The PTNullS and PTNullC scenarios generate the strongest behavioural response to flood risk. In the PTNullS scenario, average utility in flood-prone areas remains approximately 25% lower than in non-flood-prone areas throughout the simulation (Figure B9), resulting in a flood risk transaction price discount of approximately 18% by the end of the simulation (Figure

B7). Transaction activity in flood-prone areas also declines substantially after approximately ten years and becomes very limited towards the end of the simulation (Figure B8). The PTNullC scenario produces almost identical transaction prices and transaction frequencies (Figures B10 and A4), while average utility is slightly higher because households evaluate multiple flood outcomes rather than a single high flood probability. These behavioural responses are consistent with empirical evidence showing that flood risk is capitalised into housing prices and that flood-exposed properties experience lower demand and reduced market liquidity (Bin & Landry, 2013; Zhang, 2016).

The financial protection scenario, at moderate protection levels, demonstrates the expected softening influence of insurance on household decision making. Although probability weighting and loss aversion remain active, reducing the uncovered damage fraction decreases the flood risk transaction price discount to approximately 13% (Figure B11), while utility in flood-prone areas remains approximately 10% lower than in non-flood-prone areas (Figure B13). Flood zone transaction activity also remains slightly higher than under the PTNull scenarios (Figure B12). This behaviour is consistent with studies showing that insurance and financial compensation reduce the perceived consequences of flooding and influence households' willingness to pay for protection against flood losses (Botzen & Van den Bergh, 2012; De Koning et al. 2019).

The expected market value scenario produces similar market response to the PTNull scenarios. Flood-prone properties sell for approximately 19% less than comparable non-flood-prone properties by the end of the simulation (Figure B14), while household utility remains approximately 25% lower throughout the simulation (Figure B16). In this reference point formulation, households evaluate potential flood losses relative to anticipated future market values, making losses more salient than under the alternative reference point formulations. However, diminishing sensitivity to absolute utility values results in outcomes similar to those of the event-based loss formulation. This behaviour is consistent with reference-dependent preferences described by prospect theory and with empirical evidence showing that loss aversion and anchoring influence pricing behaviour within real estate markets (Genesove & Mayer, 2001; Bokhari & Geltner, 2011).

Finally, the dynamic risk scenarios reproduce the expected influence of flood experience on household risk perception. Following a distant flood event, flood-prone properties exhibit an approximately 11% transaction price discount (Figure B17), whereas a recent flood increases this discount to approximately 18% (Figure B20). The recent flood scenario also produces lower utility (Figure B22) and lower transaction activity (Figure B21) than the distant flood scenario (Figures B19 and B18), indicating that recent flood experience temporarily amplifies perceived flood risk.

This behaviour closely matches empirical studies showing that flood events temporarily increase risk perception and willingness to take protective action, after which these behavioural responses gradually diminish as flood memories fade (Bin & Landry, 2013; Gallagher, 2014; Pryce et al., 2011). Moreover, Haer et al. (2017) demonstrate in an agent-based flood risk model that incorporating dynamic risk perception and prospect theory leads to substantially different

household adaptation behaviour compared with expected utility assumptions, supporting the behavioural mechanisms implemented in the present model.

Overall, the behavioural responses generated by the model are consistent with both prospect theory and empirical observations from flood-exposed housing markets. Across all scenarios, behavioural changes in flood risk perception are systematically translated into lower utility, reduced willingness to pay, lower transaction prices and lower market activity in flood-prone areas. The direction and relative magnitude of these responses agree well with previous behavioural and empirical research, providing confidence that the implemented decision making frameworks realistically capture household responses to flood risk and are suitable for the subsequent scenario analyses.

Model limitations

A limitation of the present model is the implemented bid price formulation. Transaction prices are generated through a sequential pricing process in which the realtor first estimates a property's market value, sellers subsequently derive an asking price from this estimate, and households formulate bids relative to the asking price. Although this approach provides stable price formation and realistic market dynamics, it also introduces price anchoring, as bids remain partly dependent on the realtor's initial valuation, thereby limiting the diversity of bidding behaviour that may occur in real housing markets. Furthermore, the realtor's hedonic pricing model gradually becomes less accurate as the simulation progresses, reflecting the increasing difficulty of predicting transaction prices under evolving market conditions. Consequently, asking prices may deviate from households' willingness to pay during the later stages of the simulation, which may partially influence the observed transaction prices and reduce the model's ability to capture dynamic changes in market valuations.

In general, the validation demonstrates that the model reproduces plausible housing market dynamics and household responses to flood risk that are consistent with both behavioural theory and empirical observations. Despite several modelling simplifications, the model provides a sufficiently realistic representation of household decision making and housing market behaviour to support the subsequent scenario analyses.

Results

This chapter presents the results of 60 scenario combinations used to examine how alternative reference point formulations influence housing market dynamics under varying flood risk and housing demand conditions. Ten reference point formulations are each evaluated under medium and high housing demand pressure and annual flood probabilities of 2%, 3%, and 5%. Every model run is simulated over a 30 year time period with 2 model steps per year. To account for stochastic variation and provide robust estimates of the model outcomes each scenario is tested with 50 independent Monte Carlo simulations. An overview of the model's key parameters, values and distributions can be found in Table 3.

The results in this section are divided into two complementary categories. First, housing market outcomes are assessed through final market prices, household utility and the fraction of properties sold in flood-prone and non-flood-prone areas. Second, household spatial sorting is examined by comparing the distribution of income groups, loss aversion characteristics and probability weighting characteristics between the two flood zones. Together, these outcomes show both the aggregate effects on housing market performance and the distributional consequences for different household groups. The outcomes are initially presented separately to establish the main patterns across reference points, flood probabilities and demand conditions. They are subsequently analysed jointly across variables and scenarios to identify relationships between household behaviour, market performance and spatial sorting, thereby developing a more complete interpretation of the simulation results.

Housing market outcomes

The housing market results examine how flood exposure is reflected in both economic and behavioural outcomes. Comparing flood-prone with non-flood-prone properties reveals how risk is capitalised into transaction prices and household utility. Transaction frequency is also analysed to determine whether flood risk affects market liquidity and households' ability or willingness to complete transactions. Together, these indicators show how alternative reference points influence property valuation, household preferences and market functioning under different conditions.

Transaction prices

Transaction prices provide a direct indication of how flood risk and household reference points become capitalised into housing-market values. Table 7 presents the final average transaction prices for non-flood-prone and flood-prone properties across the ten reference-point formulations. The columns headed 2%, 3% and 5% represent the annual flood probabilities applied to properties within the flood-prone zone. For each probability, the table reports transaction prices in both zones as well as the standard deviation between simulations and the resulting relative flood-price discount, calculated according to the method defined in Equation 24. The table is divided into medium and high housing-demand conditions, enabling direct comparison of whether stronger demand moderates the effect of flood risk on transaction prices. These outcomes directly address the central research question by showing how alternative

reference points influence the capitalisation of flood risk into transaction prices. Since realised prices result from the interaction between household bids and seller decisions, the comparisons also reveal how buyer and seller behaviour jointly shape aggregate market outcomes.

Table 7. Final transaction prices at medium and high demand.

Demand: Medium	2%			3%			5%		
<i>Scenario</i>	Non-flood (€)	Flood prone (€)	Discount (%)	Non-flood (€)	Flood prone (€)	Discount (%)	Non-flood (€)	Flood prone (€)	Discount (%)
Base	330,826 (3,392)	289,234 (4,876)	12.6	331,630 (3,101)	285,119 (5,040)	14.0	333,012 (3,213)	280,577 (6,671)	15.7
PTNullS	337,590 (2,850)	282,466 (10,145)	16.3	338,085 (3,592)	285,023 (11,289)	15.7	339,007 (2,992)	288,306 (13,975)	15.0
PTNullC	335,576 (3,071)	279,039 (9,698)	16.8	337,120 (3,477)	281,576 (10,208)	16.5	339,389 (3,200)	285,744 (11,642)	15.8
PTEMV	336,017 (2,713)	279,098 (10,015)	16.9	336,687 (3,285)	281,131 (9,380)	16.5	338,130 (2,983)	287,683 (13,387)	14.9
PTFP low	333,970 (4,172)	282,577 (7,856)	15.4	336,072 (3,209)	279,646 (9,055)	16.8	336,459 (3,423)	280,344 (8,158)	16.7
PTFP med	332,250 (3,093)	285,635 (4,228)	14.0	333,546 (3,713)	282,738 (6,499)	15.2	335,443 (3,017)	278,752 (8,336)	16.9
PTFP high	331,509 (2,213)	294,891 (3,680)	11.0	332,175 (3,009)	291,488 (5,130)	12.2	332,541 (3,491)	285,745 (4,596)	14.1
PTDR recent	335,140 (2,808)	281,939 (10,886)	15.9	337,026 (3,309)	284,745 (9,869)	15.5	338,622 (3,055)	286,901 (13,369)	15.3
PTDR moderate	333,425 (3,627)	282,462 (5,915)	15.3	334,829 (3,445)	282,194 (7,996)	15.7	336,460 (2,946)	283,244 (9,122)	15.8
PTDR distant	331,433 (3,386)	290,000 (5,540)	12.5	332,451 (3,784)	286,294 (5,127)	13.9	333,983 (2,962)	282,187 (7,628)	15.5
Demand: High	2%			3%			5%		
Base	373,792 (3,418)	325,779 (4,399)	12.8	373,683 (3,641)	317,802 (3,828)	15.0	376,190 (3,565)	312,836 (5,349)	16.8
PTNullS	379,102 (3,527)	308,433 (9,607)	18.6	381,319 (3,777)	314,463 (9,787)	17.5	382,465 (3,839)	315,980 (11,951)	17.4
PTNullC	377,529 (4,200)	307,061 (7,610)	18.7	379,654 (3,438)	310,557 (8,859)	18.2	381,669 (4,224)	316,033 (10,879)	17.2
PTEMV	379,120 (3,007)	309,416 (7,151)	18.4	379,986 (3,094)	312,513 (9,234)	17.8	381,071 (3,430)	313,434 (11,107)	17.7
PTFP low	375,228 (3,140)	313,054 (4,706)	16.6	376,979 (3,587)	308,690 (6,569)	18.1	378,573 (3,331)	308,662 (9,476)	18.5
PTFP med	374,675 (2,852)	319,692 (3,801)	14.7	375,473 (3,130)	313,724 (4,147)	16.4	376,752 (3,059)	309,246 (6,631)	17.9
PTFP high	372,967 (3,980)	331,535 (4,764)	11.1	373,068 (3,294)	326,598 (5,837)	12.5	374,658 (3,217)	320,051 (4,541)	14.6
PTDR recent	377,888 (3,427)	309,874 (10,283)	18.0	379,942 (3,201)	313,503 (9,693)	17.5	380,113 (3,889)	316,068 (11,739)	16.8
PTDR moderate	375,548 (3,229)	312,443 (4,377)	16.8	376,226 (3,102)	310,869 (6,520)	17.4	379,410 (3,306)	312,202 (9,536)	17.7
PTDR distant	373,540 (3,203)	325,576 (3,690)	12.8	374,871 (3,662)	320,016 (4,878)	14.6	375,328 (3,518)	313,404 (6,907)	16.5

**Note. Values represent means across 50 independent Monte Carlo runs, with standard deviation between runs shown in parentheses underneath. Each run covers 30 simulated years with two model steps per year. Results refer to the final simulation year*

Table 7 shows that flood-prone properties transact at lower prices than non-flood-prone properties in every scenario. In the base scenario, the flood price discount increases from 12.6% to 15.7% under medium demand and from 12.8% to 16.8% under high demand as flood probability rises from 2% to 5%. High demand therefore increases absolute transaction prices but does not reduce the relative effect of flood exposure in the base scenario. For scenarios incorporating stronger subjective losses, however, high demand increases the discount by approximately two percentage points, indicating a stronger behavioural price response. This increase suggests that additional demand is disproportionately directed towards non-flood-prone properties, causing their prices to rise faster than flood-prone prices when perceived losses influence household valuations.

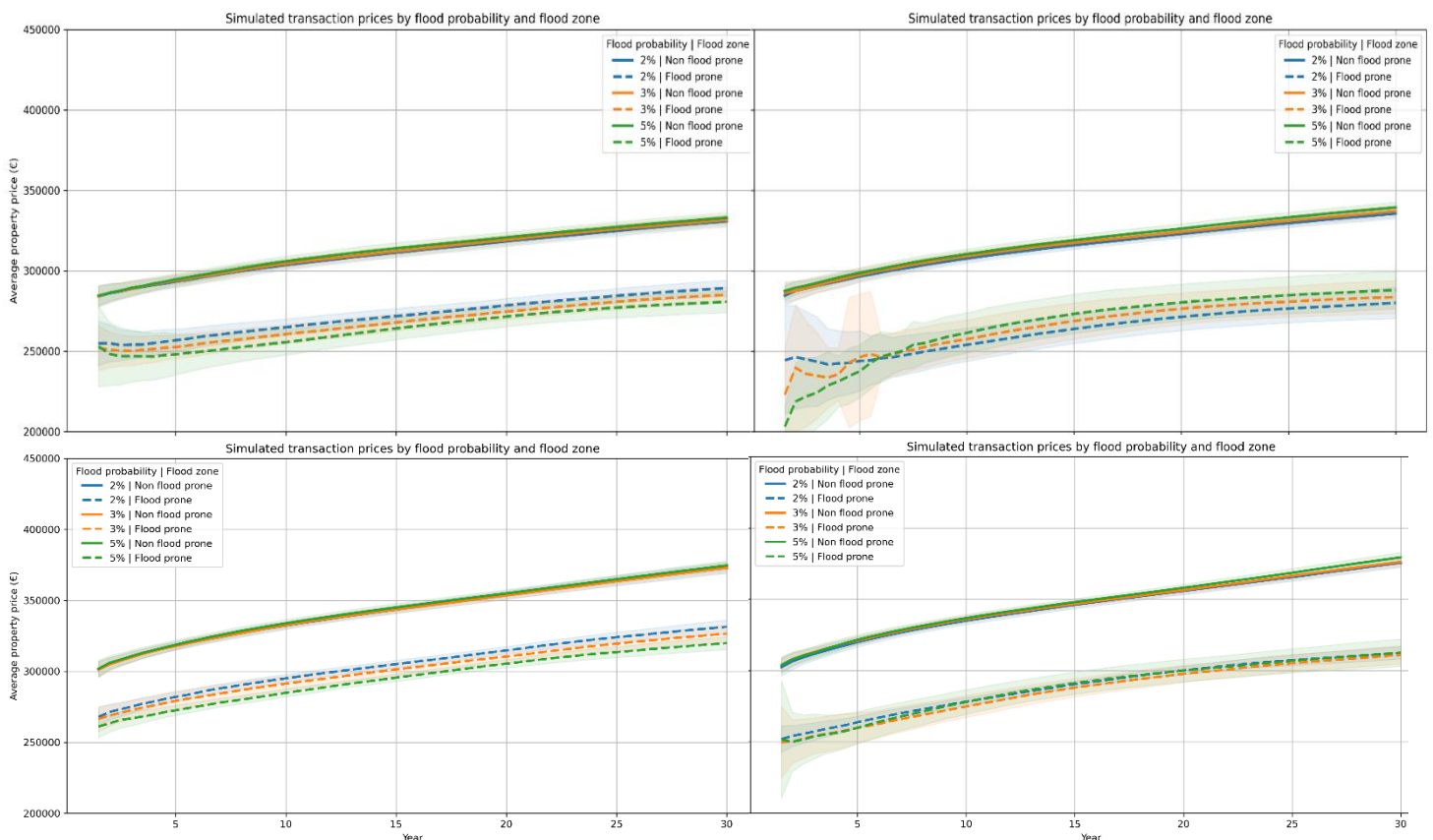


Figure 5. Transaction prices of base scenario (top left) and PTNullC (top right) under medium demand. Transaction prices of PTFP high (bottom left) and PTDR moderate (bottom right) under high demand. Graphs show the results of 50 Monte Carlo simulations of each scenario at 2,3 and 5% flood probability. Shaded areas reflect the standard deviation between runs throughout the simulation and dashed lines represent the flood-zone.

The reference point formulation substantially influences the size and development of the discount. PTNullS, PTNullC, and PTEMV produce larger discounts than the base scenario, particularly at lower flood probabilities. However, their final discounts decrease slightly as flood probability increases. The time series chart of PTNullC under medium demand in Figure 5 explains this behaviour. In scenarios with stronger perceived losses flood-prone properties are undesired at the start of the simulation. This leads to very low transaction prices as well as low transaction activity in the flood-zone which in turn causes the large standard deviations at the start of simulation. However, as prices in the non-flood-prone area start climbing demand for flood-prone properties also start to increase causing the prices to increase rapidly and standard

deviations to decrease. After a few years this causes the market to stabilise and by the end of the 30 year period flood-prone property prices at high risk (5%) exceed those under lower risk (2%) due to market dynamics.

It should be clear, however, that although the market stabilises slightly in the displayed PTNullC scenario, its final-year standard deviations remain much higher than in scenarios with lower perceived risk, such as the Base, high financial protection and distant flood experience scenarios. This indicates that the observed stabilisation is only relative and that flood-prone prices remain comparatively dependant on a small number of transactions. High financial protection and distant flood experience therefore both narrow the flood-price discount and reduce variation between runs, producing more stable price formation in the flood-prone market. Final-year standard deviations are also generally lower under high demand, particularly in the more strongly varying PTNull and PTEMV scenarios, suggesting that stronger demand and transaction activity improve the stability of flood-prone property prices.

The financial protection scenarios display the clearest pattern. Stronger expected protection produces smaller discounts, whereas limited protection widens the price difference between zones. The discount falls below the Base scenario only when expected financial protection reaches 80%, indicating that extensive compensation is required to offset subjective risk evaluation and loss aversion. Partial protection moderates but does not fully counteract these effects, leaving flood-prone properties to be transacted at higher discounts.

Dynamic risk perception produces a similar gradient. Recent flood experience generally results in larger discounts than distant experience because flood consequences remain more salient in household valuations. Distant experience brings prices closer to the Base and reduces volatility, although this reflects weaker risk awareness rather than lower exposure. Overall, variation between reference point formulations narrows sharply at the 5% flood probability. At this risk level, flood consequences are already evaluated negatively across formulations, leaving less scope for alternative reference points to influence final prices.

Taken together, these results show that reference points affect not only the price difference but also the stability of price formation. At 2% flood probability, moving from low to high financial protection reduces the discount from 15.4% to 11.0% under medium demand and from 16.6% to 11.1% under high demand. A comparable contrast appears between recent and distant flood experience, particularly under high demand, where the discount declines from 18.0% to 12.8%. These differences become smaller at 5%, confirming that behavioural assumptions matter most when objective risk remains sufficiently low for subjective framing to influence property choice. The reductions in standard deviations further indicate that weaker perceived losses support a deeper and more predictable flood-prone market. Higher demand reinforces this stabilising process through increased transaction activity, although it can simultaneously widen the discount because additional competition is concentrated in the non-flood-prone area. Increasing demand pressure therefore improves price stability without necessarily reducing spatial price inequality.

Housing utility

Housing utility represents households' subjective evaluation of properties and therefore provides insight into the behavioural mechanism underlying the observed transaction prices. Utility is recorded only when a household places a bid and is therefore calculated from bid observations rather than from all properties in the housing stock. The reported values consequently represent the average utility of properties that households actively considered suitable and affordable enough to bid on. Comparing this utility gap across reference points, flood probabilities and demand conditions directly addresses the research question by revealing how alternative reference points influence household evaluations and bidding decisions under flood risk. Table 8 presents these utility values for flood-prone and non-flood-prone properties, together with the relative utility gap. Its structure follows Table 7 and is divided into medium and high demand conditions.

Utility is consistently lower for bids on flood-prone properties, and this difference generally increases with flood probability. In the base scenario, the gap rises from 8.9% to 11.5% under medium demand and from 7.2% to 10.7% under high demand. Although absolute utility is higher under high demand, the relative utility gap remains broadly similar across the two demand conditions. This is particularly clear for PTNullS and PTEMV, where the gaps differ by no more than 0.3 percentage points between medium and high demand. Across the other scenarios, changes are also generally limited. This differs from the transaction-price results, where high demand increases the flood-price discount by approximately two percentage points in scenarios with stronger perceived losses. Greater demand increases competition and influences realised prices without substantially changing the relative utility of the properties considered. This suggests that although households' relative appreciation of properties remains similar, stronger competition under high demand forces transactions to occur at higher prices, particularly in the non-flood-prone zone.

The strongest responses occur under PTNullS. Its utility gap increases from approximately 22% at 2% flood probability to approximately 41% at 5% under both demand conditions. PTNullC and PTEMV produce a smaller but still substantial increase, reaching approximately 35% at 5% risk. Figure 6 shows how this difference develops over time. Utility for non-flood-prone bids follows a similar upward path, whereas utility for flood-prone bids remains lower and becomes increasingly separated as objective risk rises. Compared with the base scenario, this confirms that the reference-point formulation amplifies the subjective effect of flood exposure. Despite this strong subjective differentiation, the corresponding transaction-price discounts are considerably more muted. Households ultimately still seek to secure a property, and some become priced out of the non-flood-prone area as competition raises prices. Their demand is consequently redirected towards more affordable flood-prone properties, supporting transaction prices in this zone and preventing the utility disadvantage from being fully capitalised into the price gap.

Financial protection progressively reduces the utility gap. Under medium demand and 5% flood probability, the gap decreases from 19.6% with low protection to 9.1% with high protection. Under high demand, it similarly falls from 19.5% to 8.6%. As observed for

transaction prices, only the highest protection level, corresponding to 80% expected compensation, consistently produces a smaller gap than the base scenario. Figure 6 places moderate protection between the base and PTNullS scenarios throughout the simulation. The final-year standard deviations under high protection are also of a similar magnitude in both zones. Financial protection therefore both improves the relative evaluation of flood-prone properties and produces more consistent utility outcomes between runs. Nevertheless, extensive expected compensation is required to offset the subjective utility loss associated with flood exposure under Dutch prospect theory conditions.

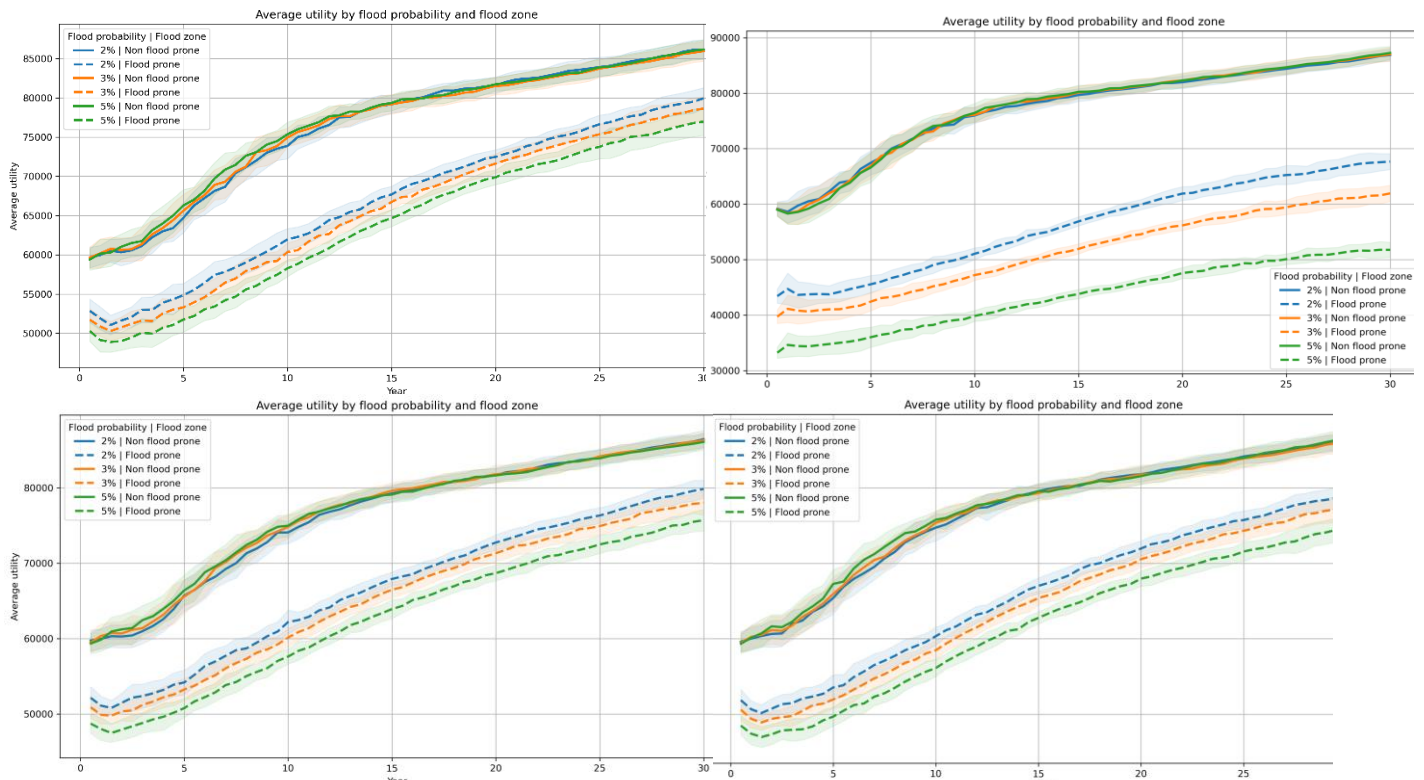


Figure 6. Utility of bids of the base scenario (top left), PTNullS (top right), PTDR distant (bottom left) and PTFP moderate (bottom right) all under high demand. Graphs show the results of 50 Monte Carlo simulations of each scenario at 2%, 3% and 5% flood probability. Shaded areas reflect the standard deviation between runs throughout the simulation and dashed lines represent the flood-zone.

Dynamic risk perception produces an equally clear ordering. Recent flood experience generates the largest utility gaps, reaching 35.0% under medium demand and 36.5% under high demand at 5% risk. Distant experience produces gaps of only 12.9% and 12.1%, while moderate experience lies between these outcomes. Figure 6 shows that utility under distant experience remains relatively close to the base scenario throughout the simulation. Unlike the transaction-price discounts, variation in utility gaps does not converge at 5% flood probability. This suggests that competition and successful market matching partly compress behavioural differences in realised prices, even though the subjective evaluations underlying placed bids remain strongly differentiated. Similar final price discounts therefore do not necessarily imply similar household perceptions of flood-prone properties.

Overall, the utility results show that reference points shape how households evaluate flood-prone properties, particularly as flood probability increases. Strong perceived losses and

recent flood experience widen the utility gap, while financial protection and distant experience may reduce it. Demand pressure changes the relative utility gaps only marginally, but market competition prevents the large subjective differences between flood zones from being fully reflected in transaction-price discounts.

Table 8. Utility of bids in final year at medium and high demand.

Demand: Medium	2%			3%			5%		
<i>Scenario</i>	Non-flood	Flood prone	Gap (%)	Non-flood	Flood prone	Gap (%)	Non-flood	Flood prone	Gap (%)
Base	76,169 (1,634)	69,391 (1,840)	8.9	76,398 (2,112)	68,669 (1,900)	10.1	76,084 (1,752)	67,372 (2,495)	11.5
PTNullS	76,635 (1,494)	59,908 (2,027)	21.8	76,657 (1,479)	54,525 (2,103)	28.9	77,003 (1,665)	45,528 (1,987)	40.9
PTNullC	76,464 (1,662)	62,807 (2,202)	17.9	76,436 (1,335)	58,840 (2,393)	23.0	77,039 (1,586)	50,308 (1,890)	34.7
PTEMV	158,601 (3,885)	131,026 (5,809)	17.4	158,344 (3,486)	121,288 (4,705)	23.4	158,864 (4,143)	104,278 (3,960)	34.4
PTFP low	76,592 (1,889)	67,546 (2,128)	11.8	76,674 (1,712)	65,377 (2,548)	14.7	76,465 (1,445)	61,503 (2,019)	19.6
PTFP med	76,142 (1,508)	69,534 (2,648)	8.7	76,561 (1,568)	67,299 (1,699)	12.1	76,351 (1,585)	65,677 (1,878)	14.0
PTFP high	76,374 (1,685)	70,896 (1,676)	7.2	76,359 (1,308)	70,202 (1,700)	8.1	76,451 (1,702)	69,481 (1,921)	9.1
PTDR recent	76,312 (1,595)	61,504 (2,408)	19.4	76,552 (1,657)	57,175 (3,034)	25.3	76,489 (1,498)	49,733 (2,503)	35.0
PTDR moderate	76,434 (1,495)	67,471 (2,554)	11.7	76,428 (1,857)	65,226 (2,501)	14.7	76,437 (1,198)	60,651 (2,986)	20.7
PTDR distant	76,432 (2,007)	69,377 (1,700)	9.2	75,920 (1,463)	68,284 (1,737)	10.1	76,076 (1,338)	66,235 (2,097)	12.9
Demand: High	2%			3%			5%		
Base	86,146 (1,184)	79,953 (1,343)	7.2	85,961 (1,291)	78,646 (1,489)	8.5	86,171 (1,251)	76,978 (1,743)	10.7
PTNullS	86,878 (1,068)	67,666 (2,386)	22.1	87,004 (1,317)	61,937 (1,391)	28.8	87,258 (1,128)	51,758 (1,363)	40.7
PTNullC	86,434 (1,297)	72,350 (2,283)	16.3	86,687 (1,156)	66,667 (2,035)	23.1	86,954 (1,317)	56,903 (1,483)	34.6
PTEMV	180,333 (2,833)	149,221 (4,110)	17.3	180,512 (3,009)	137,737 (3,116)	23.7	180,455 (2,727)	117,780 (1,855)	34.7
PTFP low	86,496 (1,157)	77,181 (1,840)	10.8	86,563 (1,307)	74,802 (2,013)	13.6	86,750 (1,137)	69,833 (1,921)	19.5
PTFP med	86,167 (1,068)	79,066 (1,538)	8.2	86,274 (1,372)	77,212 (1,700)	10.5	86,472 (1,086)	74,738 (1,670)	13.6
PTFP high	86,492 (1,556)	81,582 (1,164)	5.7	86,221 (1,233)	80,101 (1,166)	7.1	86,382 (1,072)	78,915 (1,683)	8.6
PTDR recent	86,524 (1,203)	69,903 (1,793)	19.2	86,802 (1,119)	63,705 (1,924)	26.6	86,719 (1,130)	55,079 (2,169)	36.5
PTDR moderate	86,166 (1,286)	76,834 (2,263)	10.8	86,258 (1,245)	73,495 (2,571)	14.8	87,015 (998)	68,164 (1,459)	21.7
PTDR distant	86,447 (1,141)	79,835 (1,191)	7.6	86,305 (975)	77,989 (1,596)	9.6	86,090 (1,099)	75,701 (1,444)	12.1

**Note. Values represent means across 50 independent Monte Carlo runs, with standard deviation between runs shown in parentheses underneath. Each run covers 30 simulated years with two model steps per year. Results refer to the final simulation year*

Fraction of properties sold

Transaction frequency provides insight into whether differences in flood risk perception affect not only the valuation of properties, but also the likelihood that properties are successfully exchanged. The fraction of all properties sold in the final year is calculated separately for non-flood-prone and flood-prone areas and is presented in Table 9. The activity gap represents the difference between these fractions in percentage points, with a positive value indicating lower transaction activity in the flood-prone area. Comparing this gap across reference points, flood probabilities and demand conditions directly addresses the research question by showing how buyer decisions shaped by reference points influence the likelihood of successful transactions.

Across all scenarios, the final year fraction sold is higher in non-flood-prone areas than in flood-prone areas. Under medium demand, the Base scenario produces activity gaps of 0.379, 0.401, and 0.552 percentage points at flood probabilities of 2%, 3%, and 5%, respectively. The growing gap is primarily caused by declining transaction activity in the flood-prone area, while the fraction sold outside this area remains comparatively stable. This indicates that increasing flood risk particularly reduces the liquidity of exposed properties rather than suppressing market activity uniformly across the entire housing market.

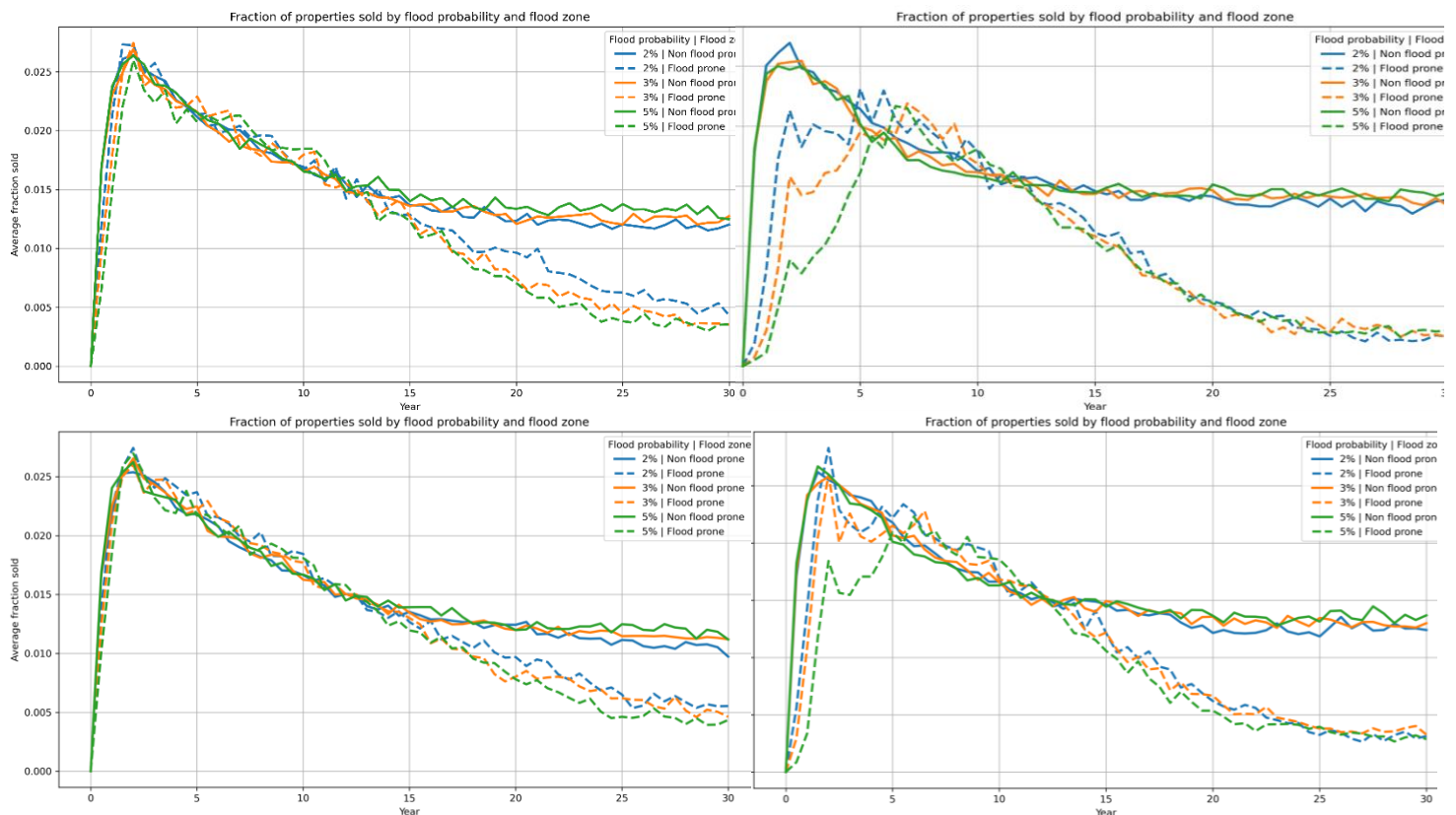


Figure 7. Fraction of properties sold of base scenario (top left), PTNullC (top right), PTFP high (bottom left) and PTDR moderate (bottom right) all under high demand. Graphs show the results of 50 Monte Carlo simulations of each scenario at 2%, 3% and 5% flood probability. Dashed lines represent flood-zone properties.

The differences between flood zones are larger under high demand. In the Base scenario, the activity gap ranges from 0.770 to 0.922 percentage points. Although higher demand increases the fraction sold in both areas, the increase is substantially stronger for non-flood-prone properties. Consequently, market pressure does not eliminate the adverse effect of flood exposure on transaction frequency. Instead, additional demand appears to be concentrated disproportionately in safer areas, thereby widening the difference in market activity between the two zones.

The PTNullS, PTNullC, and PTEMV formulations generally produce some of the largest activity gaps. Under high demand, their gaps mostly exceed one percentage point. These formulations substantially reduce the fraction of flood-prone properties sold while maintaining relatively high transaction activity outside the flood zone. This suggests that reference points incorporating subjective expected flood losses reinforce the avoidance of exposed properties and contribute to a stronger spatial separation of housing demand.

Financial protection moderates this effect. Greater expected protection consistently increases the relative transaction activity of flood-prone properties and reduces the activity gap. Under high demand, PTFP high produces gaps between 0.419 and 0.682 percentage points, which remain below the corresponding Base values at every flood probability. In contrast, limited protection produces gaps approaching or exceeding one percentage point. Expected compensation therefore supports liquidity in the flood-prone market, although it does not remove the difference between zones entirely.

A comparable pattern occurs for dynamic risk perception. Recent flood experience produces the largest activity gaps, while distant experience produces the smallest. Moderate experience generally lies between these cases. This shows that the fading salience of past flooding gradually restores transaction activity in exposed areas. Unlike the transaction price results, however, differences between reference point formulations remain clearly visible at 5% flood probability. Behavioural assumptions therefore continue to influence transaction frequency even where objective flood risk is already high.

The time-series data in Figure 7 support these final-year results and reinforce the explanation provided in the transaction-price development section. After model initialisation, flood-prone transaction activity under PTNullC initially starts at a low level but then rises sharply and temporarily exceeds activity outside the flood zone. This transition from limited activity to a short-lived surge helps explain the high initial standard deviations in transaction prices, since prices are initially formed from a small set of transactions. Flood-prone activity subsequently declines again, while activity outside the flood zone stabilises. This separation remains most pronounced under PTNullC, whereas the Base, distant risk and high financial protection scenarios retain comparatively greater activity in flood-prone areas. Higher flood probabilities further reduce flood-prone transaction activity without producing a decline outside the flood zone.

Table 9. Fraction of all properties sold in final year

Demand: Medium	2%			3%			5%		
Scenario	Non-flood (%)	Flood prone (%)	Gap (pp)	Non-flood (%)	Flood prone (%)	Gap (pp)	Non-flood (%)	Flood prone (%)	Gap (pp)
Base	0.721 (0.211)	0.342 (0.292)	0.379	0.705 (0.207)	0.304 (0.264)	0.401	0.790 (0.222)	0.238 (0.250)	0.552
PTNullS	0.850 (0.247)	0.138 (0.198)	0.712	0.850 (0.196)	0.160 (0.224)	0.690	0.845 (0.199)	0.096 (0.142)	0.749
PTNullC	0.803 (0.271)	0.187 (0.220)	0.616	0.817 (0.237)	0.107 (0.165)	0.710	0.858 (0.230)	0.138 (0.187)	0.720
PTEMV	0.786 (0.222)	0.164 (0.242)	0.622	0.861 (0.246)	0.149 (0.218)	0.712	0.891 (0.260)	0.113 (0.153)	0.778
PTFP low	0.758 (0.213)	0.187 (0.249)	0.571	0.776 (0.215)	0.207 (0.219)	0.569	0.793 (0.228)	0.133 (0.194)	0.660
PTFP med	0.708 (0.195)	0.258 (0.227)	0.450	0.704 (0.176)	0.262 (0.248)	0.442	0.757 (0.194)	0.191 (0.180)	0.566
PTFP high	0.625 (0.183)	0.342 (0.237)	0.283	0.748 (0.205)	0.316 (0.251)	0.432	0.759 (0.210)	0.222 (0.186)	0.537
PTDR recent	0.766 (0.271)	0.216 (0.239)	0.550	0.794 (0.204)	0.162 (0.236)	0.632	0.861 (0.200)	0.129 (0.166)	0.732
PTDR moderate	0.675 (0.226)	0.262 (0.273)	0.413	0.819 (0.216)	0.218 (0.261)	0.601	0.878 (0.253)	0.140 (0.186)	0.738
PTDR distant	0.691 (0.239)	0.353 (0.261)	0.338	0.758 (0.199)	0.231 (0.208)	0.527	0.768 (0.173)	0.236 (0.238)	0.532
Demand: High	2%			3%			5%		
Base	1.203 (0.289)	0.433 (0.223)	0.770	1.275 (0.279)	0.353 (0.252)	0.922	1.249 (0.234)	0.356 (0.348)	0.893
PTNullS	1.327 (0.274)	0.269 (0.340)	1.058	1.417 (0.248)	0.256 (0.331)	1.161	1.405 (0.321)	0.342 (0.368)	1.063
PTNullC	1.385 (0.299)	0.247 (0.276)	1.138	1.339 (0.280)	0.244 (0.232)	1.095	1.447 (0.314)	0.298 (0.336)	1.149
PTEMV	1.334 (0.319)	0.251 (0.282)	1.083	1.358 (0.303)	0.213 (0.283)	1.145	1.421 (0.264)	0.276 (0.249)	1.145
PTFP low	1.250 (0.269)	0.298 (0.318)	0.952	1.270 (0.308)	0.238 (0.276)	1.032	1.431 (0.314)	0.304 (0.301)	1.127
PTFP med	1.139 (0.244)	0.358 (0.236)	0.781	1.270 (0.274)	0.387 (0.359)	0.883	1.265 (0.224)	0.289 (0.261)	0.976
PTFP high	0.972 (0.231)	0.553 (0.330)	0.419	1.120 (0.219)	0.462 (0.304)	0.658	1.118 (0.237)	0.436 (0.274)	0.682
PTDR recent	1.338 (0.280)	0.298 (0.281)	1.040	1.344 (0.254)	0.269 (0.257)	1.075	1.450 (0.284)	0.267 (0.247)	1.183
PTDR moderate	1.240 (0.281)	0.313 (0.287)	0.927	1.300 (0.272)	0.327 (0.300)	0.973	1.369 (0.236)	0.287 (0.264)	1.082
PTDR distant	1.174 (0.270)	0.440 (0.309)	0.734	1.210 (0.270)	0.427 (0.269)	0.783	1.194 (0.257)	0.276 (0.281)	0.918

*Note. Values represent means across 50 independent Monte Carlo runs, with standard deviation between runs shown in parentheses underneath. Each run covers 30 simulated years with two model steps per year. Results refer to the final simulation year

One mechanism that may explain this late-stage decline is the growing mismatch between market prices and household incomes. Property prices increase throughout the simulation, while new buyers' incomes continue to be sampled from the income distribution of the current population. Figures C1 to C4 in Appendix C show that bid numbers decline to similarly low levels in both zones towards the end of the simulation. Since households only bid on properties they can afford, this pattern suggests that relatively few new buyers can afford any available property, increasingly favouring wealthier households. Among the bids that are placed, the lower utility of flood-prone properties leads to relatively lower offers against asking prices, making successful transactions less likely and helping explain the activity gap despite similar bid numbers. The very low flood-zone activity may therefore reflect both a shrinking pool of buyers able to participate and lower willingness to pay for exposed properties. The final-year differences in Table 9 consequently indicate a persistent separation in market activity between zones rather than isolated fluctuations at the end of the simulation.

Taken together, the market outcomes show that flood exposure consistently reduces transaction prices, household utility and transaction activity relative to non-flood-prone areas. The magnitude of these effects varies considerably across reference-point formulations, demonstrating that behavioural risk evaluation affects market outcomes beyond objective flood probability alone. Strong financial protection and distant flood experience generally narrow the differences between zones and reduce variation in transaction prices between runs, resulting in more stable price formation. Conversely, stronger perceived losses and recent flood experience increase utility gaps and suppress transaction activity within the flood-prone area.

The influence of behavioural formulation is most pronounced for utility and market liquidity, while transaction-price discounts become more similar at the highest flood probability. Large subjective utility differences are not fully reflected in prices because realised outcomes are also shaped by competition, affordability constraints and households' need to secure housing. Demand from households priced out of safer areas can support flood-prone prices, while the growing mismatch between prices and the current income distribution eventually reduces the number of eligible buyers. Wealthier households who remain active generally prefer non-flood-prone properties, contributing to the late-stage decline in flood-prone transaction activity. High demand therefore raises prices and transaction frequency and generally reduces price volatility, but it can also concentrate competition in safer areas and widen spatial differences in market activity.

Household spatial sorting

Household spatial sorting is examined to determine how behavioural responses to flood risk influence the socioeconomic composition of flood-prone and non-flood-prone areas. The analysis focuses on differences in income, loss aversion and probability weighting strength to identify which household groups are most likely to become concentrated in areas exposed to flooding. Understanding these patterns is important as unequal residential sorting may concentrate both physical flood exposure and financial vulnerability within certain household groups.

Income group and flood zone

Income-based spatial sorting is examined to determine whether flood risk and behavioural reference points contribute to unequal exposure across income groups, since market outcomes may conceal the concentration of lower income households in flood-prone areas. Table 10 presents homeowners across four equally sized income groups, ranging from the lowest (25%) to the highest income quartile (100%). Each value represents the share of flood-prone homeowners belonging to an income group minus the corresponding share of non-flood-prone homeowners averaged over 50 Monte Carlo simulations. Positive values indicate relative overrepresentation in flood-prone areas (blue), whereas negative values indicate overrepresentation of non-flood-prone areas (orange). Comparisons across scenarios, flood probabilities, and demand conditions reveal how reference points and market pressure influence income-based spatial sorting. Understanding this pattern contributes to the research goal by revealing whether these decisions concentrate flood exposure among households with fewer financial resources to absorb losses and recover, potentially reinforcing socioeconomic inequalities.

Table 10 reveals a consistent income-based sorting pattern across all scenarios. Additionally, final year household income levels by flood zone are reported in Appendix Table C1 to support the distributional patterns presented in Table 10. The lowest two income quartiles are overrepresented among flood-prone homeowners, while the upper two quartiles are underrepresented. This pattern is strongest for the lowest and highest income groups, indicating that flood-prone areas increasingly accommodate lower income households, whereas high income households are concentrated in non-flood-prone areas. Under the base scenario with medium demand, the difference for the lowest income quartile increases from 18.0 percentage points at 2% flood probability to 21.4 percentage points at 5%. The corresponding difference for the highest income quartile becomes more negative, changing from -20.0 to -22.4 percentage points. Higher flood probability therefore generally strengthens income-based spatial sorting. However, as observed for transaction-price discounts, differences between behavioural formulations narrow at 5% flood probability, suggesting that their additional influence on sorting diminishes as objective risk increases.

The behavioural reference point formulations produce substantially greater sorting than the base scenario. PTNullS, PTNullC, and PTEMV generate the largest concentration of lower income households in flood-prone areas, particularly under high demand. For example, under PTEMV and 5% flood probability, the lowest income quartile is overrepresented by 33.2 percentage points, while the highest quartile is underrepresented by 32.7 percentage points. The lowest income quartile in the PTNullS scenario at 2% flood risk at high demand has an increased overrepresentation of 13.5 percentage points compared to the base scenario. This indicates the overrepresentation of low income households within the flood zone has increased by 72% due to subjective perceptions.

Financial protection moderates this pattern. As the expected financial protection level increases from low to high, the differences between flood-prone and non-flood-prone areas become progressively smaller. PTFP high produces the weakest sorting across both demand

conditions and frequently results in less segregation than the base scenario. This suggests that stronger expected compensation reduces the extent to which flood risk separates households according to purchasing capacity.

Table 10. Household income group distribution, flood-prone vs non-flood-prone

Demand: Medium		2%				3%				5%			
<i>Scenario</i>	<i>Quartile</i>	Low (%)	Medium (%)	High (%)	Very high (%)	Low (%)	Medium (%)	High (%)	Very high (%)	Low (%)	Medium (%)	High (%)	Very high (%)
Base		18.0	8.3	-6.3	-20.0	19.8	9.6	-8.4	-20.9	21.4	10.6	-9.7	-22.4
PTNullS		24.8	11.5	-12.5	-23.8	25.9	10.8	-12.8	-24.0	28.4	9.3	-13.0	-24.7
PTNullC		24.4	10.7	-12.3	-22.8	25.3	11.2	-12.8	-23.6	26.9	10.8	-13.1	-24.6
PTEMV		24.4	11.3	-12.7	-23.1	24.8	12.2	-13.6	-23.5	27.3	10.2	-13.2	-24.3
PTFP low		21.3	10.4	-9.8	-21.8	24.3	10.2	-11.6	-22.9	24.6	11.1	-12.0	-23.8
PTFP med		19.6	9.4	-8.0	-21.0	21.0	9.8	-9.1	-21.7	23.4	11.2	-11.1	-23.5
PTFP high		15.9	6.8	-4.0	-18.8	17.2	8.2	-5.3	-20.1	19.5	9.6	-8.1	-21.0
PTDR recent		24.5	10.3	-12.7	-22.1	25.5	10.5	-12.9	-23.2	27.2	10.1	-13.1	-24.1
PTDR moderate		21.3	10.2	-9.7	-21.8	22.3	10.5	-10.4	-22.4	24.5	10.9	-12.1	-23.3
PTDR distant		17.9	8.3	-6.4	-19.7	19.0	9.5	-7.6	-21.0	21.8	10.1	-9.4	-22.5
Demand: High		2%				3%				5%			
Base		18.8	14.1	-7.1	-25.9	23.2	15.5	-11.2	-27.6	26.6	16.7	-12.2	-31.1
PTNullS		32.3	15.9	-18.0	-30.2	30.7	18.6	-17.6	-31.7	32.3	18.8	-18.1	-33.0
PTNullC		31.1	16.4	-17.7	-29.8	31.2	17.6	-17.2	-31.6	30.8	19.0	-16.7	-33.1
PTEMV		30.7	16.3	-16.6	-30.4	31.3	17.4	-17.2	-31.5	33.2	18.4	-18.9	-32.7
PTFP low		25.3	16.0	-12.3	-29.0	28.4	16.3	-14.2	-30.5	31.3	16.2	-15.0	-32.5
PTFP med		21.6	15.2	-9.0	-27.8	25.6	16.4	-12.8	-29.2	28.7	15.7	-13.3	-31.2
PTFP high		15.5	11.7	-3.7	-23.5	18.2	13.3	-6.0	-25.6	21.6	15.0	-8.4	-28.3
PTDR recent		30.4	16.7	-17.0	-30.1	30.2	18.3	-17.1	-31.4	30.9	18.6	-17.5	-32.0
PTDR moderate		25.7	16.1	-13.6	-28.2	27.3	16.4	-13.8	-29.8	29.2	17.7	-14.1	-32.8
PTDR distant		18.2	14.4	-6.6	-25.9	21.7	14.9	-8.7	-27.9	26.2	14.9	-11.3	-29.9

**Note. Values represent the mean percentage point difference in the share of households in each income quartile between flood-prone and non-flood-prone areas, averaged across 50 Monte Carlo runs. Blue and orange shading represent positive and negative differences. Colour intensity is scaled separately within the medium and high demand sections.*

Dynamic risk perception shows a comparable progression. Recent flood experience produces the strongest spatial sorting, moderate experience generates intermediate differences, and distant experience generally approaches the base scenario. This indicates that the declining salience of past flooding gradually reduces its influence on residential location decisions. Finally, high demand amplifies income sorting across nearly all formulations. Under constrained market conditions, lower income households appear less able to avoid comparatively affordable flood-prone properties, while wealthier households retain greater access to housing in non-flood-prone areas. The results therefore show that behavioural risk perception affects not only market prices and activity but also the distribution of flood exposure between income groups.

Overall, behavioural formulations strongly influence income-based spatial sorting, particularly at the lower objective flood probability of 2%, where differences between reference points are most pronounced. The clear overrepresentation of wealthier households in non-flood-prone areas also supports the earlier interpretation that rising property prices increasingly restrict access to safer housing towards the end of the simulation. Safety therefore appears increasingly accessible mostly to the wealthiest households, linking behavioural housing decisions to an unequal distribution of flood exposure.

Probability weighting and flood zone

Probability weighting is examined to determine whether heterogeneity in how households perceive flood probabilities contributes to household spatial sorting. Households are divided into four equally sized groups, ranging from weak to very strong probability weighting. As the standard deviation in probability weighting is relatively small, behavioural differences between these groups remain modest. Given four equally sized groups, the mean probability weighting parameter differs by approximately 0.064 between the two extreme quartiles. This corresponds to approximately 8% of the mean weighting parameter. Table 11 presents the average difference in representation of these groups between flood-prone and non-flood-prone homeowners over 50 independent Monte Carlo simulations. Positive values indicate relative concentration in the flood-prone area, whereas negative values indicate relative concentration in the non-flood-prone area. For PTNullS, households are classified using the loss weighting parameter applied within its utility formulation, whereas the gain weighting parameter is used for the other scenarios.

The Base scenario does not incorporate probability weighting into household decisions. Consequently, the small differences between its weighting groups reflect stochastic variation and no systematic sorting pattern is expected. In the behavioural scenarios, however, a consistent gradient is visible under both demand conditions. Households with weak probability weighting are generally overrepresented among flood-prone homeowners, while households with very strong weighting are more frequently concentrated in non-flood-prone areas. This pattern is already apparent under medium demand pressure, despite the modest magnitude of individual values. At 2% flood probability, all prospect theory behavioural scenarios show a positive value for weak weighting and a negative value for very strong weighting. This pattern is behaviourally consistent with the theory, households that have a stronger overestimation of flood risk actually choose to live in safe areas whereas households that experience weaker exaggeration of risk end up in the flood-prone area more often.

The sorting gradient becomes more pronounced under high demand pressure, suggesting that competition for safe properties amplifies the spatial consequences of relatively small differences in risk perception. The clearest example occurs under PTDR distant at 2% flood probability, where values range from +1.76 percentage points for weak weighting to -1.74 for very strong weighting. This produces a separation of 3.50 percentage points between the extreme groups. Because the awareness of flood risk and past experience has largely faded in this formulation, overall perceived risk is comparatively low. Probability weighting therefore accounts for a much larger share of the remaining perceived losses and variation in household risk perception and becomes more influential in residential location decisions.

Table 11. Probability weighting strength household distribution, flood-prone vs non-flood-prone

Demand: Medium		2%				3%				5%			
<i>Scenario</i>	<i>Quartile</i>	Weak (%)	Medium (%)	Strong (%)	Very Strong (%)	Weak (%)	Medium (%)	Strong (%)	Very Strong (%)	Weak (%)	Medium (%)	Strong (%)	Very Strong (%)
Base		-0.53	0.41	-0.05	0.18	-0.11	0.31	0.05	-0.25	-0.33	-0.17	0.54	-0.03
PTNullS		0.66	0.09	-0.70	-0.04	0.45	0.09	-0.18	-0.36	-0.03	-0.32	0.31	0.04
PTNullC		0.64	-0.07	0.12	-0.68	0.23	0.30	-0.38	-0.16	0.22	-0.22	0.01	-0.01
PTENV		0.60	-0.19	0.15	-0.55	0.04	-0.05	0.05	-0.04	0.32	-0.10	0.09	-0.31
PTFP low		0.59	0.10	0.28	-0.98	0.00	0.34	-0.06	-0.28	0.13	-0.09	0.17	-0.21
PTFP med		0.64	-0.13	-0.08	-0.43	0.42	0.22	-0.31	-0.32	0.30	0.67	0.09	-1.05
PTFP high		0.64	0.06	0.25	-0.95	0.48	0.23	-0.72	0.00	0.49	-0.15	-0.08	-0.26
PTDR recent		0.69	-0.03	-0.03	-0.63	-0.24	0.08	0.19	-0.03	0.64	-0.14	-0.38	-0.13
PTDR moderate		0.63	0.09	-0.14	-0.59	0.08	0.77	-0.11	-0.74	0.04	0.37	0.00	-0.40
PTDR distant		0.76	0.63	-0.42	-0.97	0.83	0.17	-0.04	-0.96	0.60	0.19	-0.32	-0.48
Demand: High		2%				3%				5%			
Base		-0.02	0.25	-0.25	0.02	0.37	-0.23	-0.20	0.05	-0.44	0.21	-0.21	0.44
PTNullS		0.92	-0.10	0.16	-0.98	0.39	0.46	-0.55	-0.30	0.34	0.16	0.13	-0.64
PTNullC		0.61	0.22	-0.19	-0.63	0.39	0.10	-0.05	-0.43	0.04	0.51	-0.37	-0.19
PTENV		0.96	0.06	-0.29	-0.73	0.64	0.52	0.07	-1.23	-0.10	-0.07	-0.17	0.34
PTFP low		0.60	0.12	-0.13	-0.59	0.84	0.02	-0.09	-0.77	0.25	0.21	0.08	-0.54
PTFP med		1.18	0.13	-0.15	-1.15	1.02	-0.03	-0.42	-0.57	0.60	0.12	-0.40	-0.32
PTFP high		0.91	0.66	-0.52	-1.05	0.53	0.57	-0.15	-0.96	0.45	-0.02	0.32	-0.75
PTDR recent		0.86	-0.21	0.00	-0.65	0.25	0.03	-0.02	-0.27	0.56	0.07	-0.43	-0.20
PTDR moderate		1.09	0.47	-0.28	-1.28	0.65	-0.12	0.12	-0.65	0.46	0.38	-0.46	-0.39
PTDR distant		1.76	0.40	-0.41	-1.74	1.16	0.48	-0.32	-1.32	0.83	0.06	0.10	-0.98

*Note. Values represent mean percentage point differences in probability-weighting quartile shares between flood-prone and non-flood-prone areas across 50 Monte Carlo runs. Blue indicates greater representation in flood-prone areas and orange indicates lower representation. Colour intensity reflects absolute differences and is scaled separately for each demand condition.

The differences between weighting groups and reference point formulations generally become smaller as objective flood probability increases. Under high demand, the separation between the weak and very strong groups in PTDR distant decreases from 3.50 percentage points at 2% flood probability to 2.48 at 3% and 1.81 at 5%. Similar convergence is visible in several other formulations, although it is not uniform across every scenario. This corresponds with the transaction price results, market activity and income-based sorting. At 5% objective flood probability, flood exposure is already perceived sufficiently negatively across households that alternative reference points and small differences in probability weighting provide less additional differentiation. Objective risk increasingly dominates household evaluations, causing the behavioural outcomes to converge.

Overall, probability weighting contributes to systematic spatial sorting under both demand conditions. The effect strengthens when competition for safe properties increases and is most pronounced when other components of perceived flood risk are relatively weak. At

higher objective flood probabilities, the influence of weighting strength and reference point selection generally diminishes as objective flood exposure becomes the dominant consideration in household location decisions.

Loss aversion and flood zones

Loss aversion provides a second behavioural dimension through which household risk preferences may influence spatial sorting. The loss aversion coefficient (λ_i) is normally distributed across households with a mean of 1.47 and a standard deviation of 0.0765. Households are divided into four equally sized groups according to their coefficient, ranging from weak to very strong loss aversion. This corresponds to an approximate difference of 0.19 in the average coefficient between the two extreme quartiles, or around 13% of the loss aversion mean population value. Table 12 reports the percentage point difference between the share of each loss aversion group among flood-prone and non-flood-prone homeowners averaged over 50 independent Monte Carlo simulations. Positive values therefore indicate relative concentration in the flood-prone area, while negative values indicate concentration in the non-flood-prone area.

The base scenarios show no clear sorting by loss aversion, as expected, since households evaluate objective flood probabilities without incorporating loss aversion into their decisions. Across the behavioural scenarios, however, a general sorting gradient emerges. Households with weak loss aversion are more frequently overrepresented among flood-prone homeowners, whereas households with very strong loss aversion tend to be overrepresented in non-flood-prone areas. This relationship is particularly consistent under high demand pressure. At 2% flood probability, for example, all behavioural formulations show a positive difference for the weak loss aversion group, ranging from +0.36 to +1.01 percentage points, while the very strong group is negative in every case.

The strongest separation occurs for PTFP high, where the difference ranges from +0.96 percentage points for weakly loss averse households to -0.94 for very strongly loss averse households. This pattern is consistent with the theoretical role of loss aversion: households that attach greater weight to potential losses have a stronger incentive to avoid flood exposure and choose non-flood-prone properties, provided that they can afford them. Similar strong sorting is visible for the financial protection scenarios, particularly PTFP low and high. Under medium demand the same underlying tendency remains visible, although individual cells show greater variation and the gradient is less consistent.

Increasing demand pressure generally strengthens the spatial expression of loss aversion. When competition for housing is higher, differences in households' willingness to accept flood related losses become more consequential for where they ultimately locate. Weakly loss averse households are comparatively more willing to accept flood-prone properties, while strongly loss averse households preferentially sort towards safer locations. Increasing objective flood probability does not eliminate this relationship, although the distinction between groups becomes less consistent in several formulations at 5% risk as objective flood exposure becomes increasingly dominant in household evaluations.

Table 12. Loss aversion strength household distribution, flood-prone vs non-flood-prone

Demand: Medium		2%				3%				5%			
<i>Scenario</i>	<i>Quartile</i>	Weak (%)	Medium (%)	Strong (%)	Very Strong (%)	Weak (%)	Medium (%)	Strong (%)	Very Strong (%)	Weak (%)	Medium (%)	Strong (%)	Very Strong (%)
Base		0.07	0.06	-0.12	-0.01	-0.02	-0.51	0.37	0.17	-0.05	-0.28	0.19	0.13
PTNullS		0.34	-0.01	-0.11	-0.22	0.18	-0.02	-0.07	-0.09	-0.01	0.18	-0.17	-0.01
PTNullC		0.21	0.05	-0.01	-0.26	-0.14	-0.12	0.20	0.06	0.18	0.14	0.06	-0.39
PTEMV		0.21	-0.02	-0.28	0.09	0.34	-0.41	0.16	-0.09	-0.04	0.53	0.12	-0.61
PTFP low		0.01	0.50	0.04	-0.54	0.26	0.23	0.30	-0.80	-0.28	0.42	0.09	-0.23
PTFP med		0.57	0.40	-0.62	-0.35	0.44	-0.03	-0.06	-0.35	0.22	-0.09	0.29	-0.42
PTFP high		0.49	-0.02	-0.01	-0.46	0.75	-0.68	0.23	-0.31	0.22	0.19	0.11	-0.52
PTDR recent		0.25	-0.43	0.31	-0.13	0.11	-0.07	-0.04	0.01	0.28	-0.34	0.33	-0.27
PTDR moderate		0.24	0.21	0.20	-0.65	0.06	0.20	0.16	-0.42	0.21	0.07	-0.38	0.09
PTDR distant		0.53	0.11	-0.65	0.00	0.59	0.03	-0.17	-0.45	0.39	0.22	-0.07	-0.54
Demand: High		2%				3%				5%			
Base		0.13	0.16	-0.03	-0.26	-0.17	-0.18	0.35	0.00	0.31	0.00	-0.25	-0.05
PTNullS		0.43	0.12	-0.17	-0.38	0.63	-0.07	-0.37	-0.18	0.35	0.12	-0.58	0.10
PTNullC		0.54	-0.05	-0.18	-0.32	0.55	-0.05	-0.23	-0.27	0.30	0.21	-0.03	-0.49
PTEMV		0.53	-0.22	0.18	-0.48	0.49	0.22	-0.43	-0.27	0.16	0.17	0.31	-0.64
PTFP low		0.96	0.08	-0.33	-0.71	0.35	0.00	0.16	-0.51	0.46	0.39	-0.24	-0.62
PTFP med		0.67	-0.08	-0.12	-0.47	0.97	0.26	-0.47	-0.77	0.36	-0.09	-0.16	-0.10
PTFP high		0.96	0.57	-0.59	-0.94	0.39	-0.07	0.19	-0.51	0.64	0.24	-0.24	-0.64
PTDR recent		0.52	0.22	0.02	-0.77	0.39	0.47	-0.42	-0.44	0.53	0.08	0.25	-0.86
PTDR moderate		0.36	0.10	-0.13	-0.33	0.44	-0.05	-0.31	-0.08	0.62	-0.21	0.00	-0.41
PTDR distant		1.01	-0.50	0.09	-0.59	0.96	-0.07	-0.11	-0.78	0.65	-0.19	0.18	-0.63

*Note. Values represent mean percentage point differences in loss-aversion quartile shares between flood-prone and non-flood-prone areas across 50 Monte Carlo runs. Blue indicates greater representation in flood-prone areas and orange indicates lower representation. Colour intensity reflects the absolute difference and is scaled separately within each demand condition.

An important difference appears when loss aversion is compared with probability weighting. The approximately 13% difference in the loss aversion coefficient between the extreme quartiles is larger in relative terms than the parameter differences between the probability weighting groups. Nevertheless, the resulting spatial differences are generally smaller than those observed for probability weighting. Although the parameters enter household decisions differently and are therefore not directly comparable, the results suggest that probability weighting is associated with stronger residential sorting than loss aversion within the tested parameter ranges. Larger relative differences in behavioural parameters therefore do not necessarily produce stronger spatial sorting, highlighting the importance of how each parameter enters household valuations and which circumstances. Loss aversion therefore contributes to spatial sorting, but plays a more modest role in determining which households reside in flood-prone areas.

Synthesis and interpretation of results

The combined results demonstrate that reference-point formulation strongly influences how flood risk translates into housing market outcomes through multiple channels. PTNullS, PTNullC and PTEMV generally caused stronger differences between flood zones in utility, transaction activity and income composition, alongside larger price discounts at lower flood probabilities compared to the objective risk baseline. These effects show that identical objective exposure can produce different outcomes depending on how households define and evaluate potential losses. Expected financial protection and fading flood experience moderate these responses through different mechanisms: protection reduces the expected uncovered financial losses, whereas distant experiences reduce the attention given to flood risk. Only the highest tested compensation level of 80% consistently reduces price and utility gaps below the Base scenario, while distant experience generally brings aggregate market outcomes close to it. Reference-point selection therefore has substantive consequences for model results and cannot be treated as an interchangeable specification choice. The comparison identifies influential behavioural assumptions without establishing which formulation best represents actual household decisions.

The effects develop through interactions between household preferences and changing market conditions. Figures 5 through 7 show that flood-prone properties initially attract few transactions when perceived losses are strong, particularly under PTNullC, PTNullS and PTEMV. This results in large differences in transaction prices between simulation runs due to the small number of registered transactions. As prices outside the flood zone rise, cheaper flood-prone properties become attractive to households unable to afford safer alternatives. As a result, flood-prone activity temporarily increases, supporting price growth despite the lower subjective utility of these properties. The model's bidding mechanism and inflow of new buyers also influence this relationship because offers depend on asking prices as well as utility. Price discounts therefore are not necessarily as large as utility gaps. Later, flood-prone activity declines while activity outside the flood zone stabilises. One possible explanation is that prices rise faster than household purchasing power, leaving fewer households able to buy and favouring wealthier buyers who can afford safer properties anyway. The final income distributions support this interpretation, although they do not identify buyers' incomes at each stage. Together, these findings suggest that growing prices in the flood-zone do not necessarily mean that transaction activity or household appreciation has fully recovered.

Higher demand strengthens these differences between flood zones. It raises transaction prices and activity in both areas, but generally increases price discounts and income sorting as competition is concentrated more strongly in non-flood-prone areas. Relative utility gaps change comparatively little, suggesting that stronger demand mainly changes the prices households pay and where they can afford to live. Meanwhile, final-year price standard deviations are generally lower under high demand, showing more consistent outcomes between runs, although not necessarily smaller price fluctuations within individual simulations. Increased activity and more consistent prices therefore do not guarantee more equal access to safer housing. Understanding market outcomes requires considering both how properties are traded and which households ultimately remain exposed to flooding.

The income patterns in Table 10 show that flood exposure is distributed unequally between household groups. Lower-income homeowners are more strongly represented in flood-prone areas, while wealthier households are concentrated outside them. This raises a question of distributive justice: access to safer housing depends partly on purchasing power, potentially leaving households with fewer resources to recover from damage more exposed. Behavioural sorting adds another dimension to this, with probability weighting showing clearer differences than loss aversion within the tested parameter ranges. Notably, distant flood experience brings overall market outcomes close to the Base scenario while still producing clear sorting by behavioural characteristics. Similar prices and transaction activity can therefore conceal differences in who occupies each zone. A return towards baseline outcomes should consequently not be interpreted as the disappearance of behavioural effects. Nor do smaller discounts indicate reduced physical exposure, since fading awareness changes how households evaluate the hazard rather than physically reducing the hazard itself.

The influence of reference-point formulation also depends on objective flood probability and the outcome being examined. As annual risk rises from 2% to 5%, differences between formulations generally narrow for transaction-price discounts and several sorting patterns. One interpretation is that higher objective risk makes flood exposure unattractive under a wider range of behavioural assumptions, leaving less scope for alternative reference points to produce different outcomes. However, utility gaps remain strongly differentiated, and differences in transaction activity also persist. The convergence of prices therefore provides only partial evidence that objective risk becomes more influential. It does not establish that subjective evaluations become identical or that behavioural assumptions cease to matter. This distinction highlights the value of examining prices, utility, transactions and household composition together, because each reveals a different part of the response to flood risk.

These findings connect the strands of literature discussed earlier. The effects of distant flood experience are consistent with research describing how housing market responses weaken as memories of flooding fade (Bin & Landry, 2013; Pryce et al., 2011). Differences between formulations also support the importance of considering alternative reference points in housing decisions (Tomal, 2024b). Building on the connection between household decisions and market outcomes provided by agent-based modelling (Filatova, 2014), this study compares these formulations within a common market setting. Its contribution is to show how different ways of evaluating the same objective risk can be formulated and how these formulations affect both market outcomes and the distribution of exposure among households, and why prices alone provide an incomplete picture. These findings help answer the central research question and identify mechanisms for future empirical research. However, the findings always depend on how the model represents household behaviour, bidding and other assumptions. The following section discusses these limitations and opportunities for further research.

Model limitations and future research directions

Before drawing the final conclusions, several limitations of the model and experimental design must be considered when interpreting the results. These limitations concern the behavioural assumptions, representation of the housing market and uncertainty surrounding the selected parameter values.

Research limitations and contextual boundaries

The findings should be interpreted as evidence of mechanisms and relative differences between scenarios rather than as precise forecasts of future housing-market outcomes in Limburg. The agent-based model necessarily simplifies the behaviour of households, properties and market institutions to isolate the influence of prospect theory reference points. Although this controlled design supports comparison between formulations, it cannot represent the full complexity of real housing decisions, in which location preferences, employment, household composition, mortgage conditions and social ties may interact with flood risk.

The behavioural parameters for probability weighting and loss aversion were derived from existing literature rather than estimated specifically for households in the Limburg river area. Their distributions introduce meaningful household heterogeneity, but assume that these parameters remain stable throughout the simulation. In reality, risk preferences may change following new information, personal experience or changes in financial circumstances. The reference-point formulations are also evaluated separately, whereas households may simultaneously consider expected appreciation, compensation, previous flood experience and other benchmarks. Consequently, the results isolate the effect of each reference point formulation but do not capture how households may combine several benchmarks within a single housing decision.

Flood risk is represented through fixed annual probabilities of 2%, 3% and 5% and a distinction between flood-prone and non-flood-prone properties. This allows objective risk levels to be compared consistently, but does not capture variation in flood depth, damage severity, local protection standards or risk within each zone. No new flood event occurs during the simulation. Consequently, the dynamic-risk scenarios represent the gradual decline of an initial perception shock, but not repeated updating after additional floods. The lowest tested probability of 2% is also relatively high, which may partly explain why differences between reference-point formulations already narrow as risk increases.

The behavioural extensions primarily concern buyers' utility calculations, bidding and property selection. Market valuation, asking prices, bid evaluation and transaction registration remain inherited from the existing model. These processes provide a stable market environment, but their assumptions may limit changes to behavioural demand and seller responses. A related limitation concerns the calibrated mapping from household utility to bid prices. Although utility differences influence property rankings and the magnitude of submitted bids, the bidding

factors remain bounded and are anchored to the asking price to maintain realistic transaction rates and stable market dynamics. This constrains the extent to which large differences in perceived utility can translate into monetary offers. Behavioural differences between reference point formulations may therefore be partly dampened at the transaction price level. Future research could estimate this relationship using empirical bidding or transaction data, allowing the monetary response to behavioural utility differences to emerge with fewer imposed constraints.

Housing demand is represented through medium and high demand settings rather than emerging from demographic change, migration, credit conditions or macroeconomic developments. Public flood defences, insurance, household adaptation and actual compensation decisions are also not modelled directly. Anticipated financial protection should therefore be interpreted as a household belief about expected compensation rather than a complete representation of Dutch disaster-relief arrangements.

Finally, averaging outcomes across 50 Monte Carlo runs reduces the influence of random variation but does not remove structural uncertainty. Verification indicates that the implemented mechanisms operate as intended, while validation shows that the model produces plausible patterns and market outcomes. However, few empirical studies directly identify which reference points households use when evaluating flood prone properties or measure how these reference points affect decisions over time. The model therefore explores possible reference point mechanisms rather than predicting the magnitude of their effects or demonstrating which mechanisms households use in practice.

Future research directions

Building on these limitations, future research should examine whether the identified behavioural mechanisms remain consistent across different geographical, institutional and cultural settings. The values and effects of loss aversion and probability weighting may vary between populations, while compensation arrangements, insurance systems and housing-market conditions can alter the reference points used by households. Applying the model to other flood-prone regions with locally calibrated parameters would show which findings are transferable and which are specific to the Limburg river area.

Further research could examine reference-point effects under lower objective flood probabilities resulting from public flood defences. The lowest probability tested in this study was 2%, which already represents considerable annual risk. Since differences between reference-point formulations were most visible at lower risk and converged as objective risk increased, scenarios below 2% may reveal stronger behavioural variation. Public protection could be represented through reductions in flood probability, expected damage or both.

A particularly important next step is to identify empirically which reference points households actually use when evaluating flood-prone properties. Existing literature provides limited direct evidence on whether buyers focus on expected flood losses, individual flood events, future property value, anticipated compensation or previous flood experience. Surveys, choice experiments and interviews with recent homebuyers could be used to compare these

alternatives. Longitudinal research could subsequently examine whether reference points and perceived risk change after floods, long periods without flooding or new information about compensation and public protection. These findings would support more accurate parameterisation and validation of behavioural housing-market models.

Finally, future models could allow households to consider several reference points simultaneously rather than evaluating each formulation separately. The importance assigned to each benchmark could change with income, experience and market conditions. Introducing realised flood events, household level risk reduction measures and changing protection policies would also allow risk perceptions and housing decisions to evolve within the model. These extensions would provide a more complete account of how behavioural responses interact with physical protection and housing-market dynamics over time.

These limitations and research opportunities define the scope within which the findings should be interpreted. Taking these limitations and opportunities into account, the following chapter presents the study's conclusions, policy recommendations and contributions to science and society.

Conclusions and recommendations

Following the synthesis of results and the identified model limitations, this chapter presents the final conclusions of the study. The identified limitations are treated as contextual conditions when interpreting the findings and formulating recommendations. The chapter first answers the main research question and supporting sub-questions based on the combined theoretical and model findings. The policy implications are then translated into recommendations for the actors identified in the stakeholder analysis, while distinguishing between findings supported by the model and interventions that were not directly simulated. Finally, this chapter reflects on the scientific and societal contributions of the research, positioning the behavioural model extensions and resulting insights within the wider study of housing decisions and flood related vulnerability.

Answering the research questions

The research questions are answered by combining insights from the literature, model development and simulation results. Each sub-question is addressed sequentially, after which the combined findings are used to answer the main research question.

SQ1: How do flood risk, housing market dynamics and individual decision making interact in riverine regions under increasing climate pressure?

This sub-question delineates the housing market as a system in which physical flood exposure, household decisions and market processes interact. Households evaluate available properties according to affordability, location, expected utility and perceived flood risk, while sellers and realtors determine asking prices and market values using property characteristics and previous transactions. Buyers' evaluations are translated into bids, and completed transactions subsequently update market prices and influence later decisions. Increasing flood

risk lowers the relative attractiveness of exposed properties, but its market effect depends on housing demand, household purchasing power and individual risk perception. These interactions create feedback between household choices and aggregate outcomes: individual preferences affect prices, transaction activity and residential sorting, while emerging market conditions constrain the properties households can obtain. This system representation provides the conceptual basis for identifying where behavioural assumptions enter the model.

SQ2: How do behavioural factors, including risk perception, loss aversion and reference dependence, influence housing decisions under flood risk?

Behavioural factors influence housing decisions by changing how households evaluate the likelihood and consequences of flooding. This sub-question establishes the theoretical foundations used to represent these decision processes in the model. Prospect theory explains that households evaluate outcomes as gains or losses relative to a reference point rather than through absolute property value alone. Loss aversion gives potential flood damage greater influence than an equivalent gain, while probability weighting causes low probability events to be perceived differently from their objective likelihood.

Expectations of property value growth can raise the reference point, causing households to evaluate flood damage against the anticipated future market value of a property. Flood risk myopia and amnesia add a temporal dimension: recent flood experience increases risk salience, whereas prolonged periods without flooding allow perceived risk to decline. Expected financial protection can further reduce the portion of damage regarded as a personal loss. Together, these mechanisms influence utility, willingness to pay and location choice by changing how households interpret the likelihood and consequences of flooding.

SQ3: How can different prospect theory reference points for buyers be defined and operationalised in housing market decision making under flood risk?

The behavioural mechanisms were operationalised by extending the Dutch riverine adaptation of the RHEA housing market model developed by Mutlu and Filatova (2026). As shown by the introduced and adapted processes in Figure 3, households are assigned heterogeneous prospect theory parameters during initialisation using the parameter values presented in Table 3. This introduces individual differences in loss aversion and probability weighting among households. When searching for properties, buyers evaluate affordable listings according to perceived flood risk and calculate reference-dependent utility. The reference point varies between a single expected flood loss, event-based flood losses, expected future market value and three levels of anticipated financial protection. Three flood experience levels represent the effects of flood risk myopia and amnesia.

The resulting utility is translated into bid prices through the calibrated bidding mechanism, directly connecting behavioural evaluation to property selection and market interaction. Because bidding factors are bounded and anchored to asking prices, this translation preserves realistic market dynamics while constraining the extent to which large utility differences are expressed in monetary bids. Market valuation, seller pricing, bid evaluation and

transaction registration remain inherited from the existing model, with the behavioural extensions incorporated into the original model structure.

SQ4: How do differences in reference points and behavioural assumptions influence housing market outcomes under flood risk in the Limburg river area?

This sub-question integrates the preceding system, behavioural and model development insights by connecting individual buyer evaluations to aggregate housing market outcomes. Across the scenarios, flood-prone properties generally recorded lower utility, transaction prices and transaction frequency than properties outside the flood zone. The magnitude of these differences varied between reference point formulations. Only anticipated financial protection of 80% reduced adverse market outcomes below those produced under objective risk perception, while distant flood experience generated outcomes closest to the Base scenario. Differences between formulations were most visible at lower flood probabilities and generally narrowed at 5% risk for transaction prices and sorting patterns. High demand increased market activity and prices but also strengthened spatial sorting. Lower income households became more concentrated in flood-prone areas, while households with greater purchasing power and stronger behavioural responses to risk were more frequently located outside them. Reference point selection therefore affects both market performance and the distribution of flood exposure.

Main research question

How do different prospect theory reference points influence individual housing decisions and resulting market outcomes under flood risk in the Limburg river area?

Different prospect theory reference points influence housing decisions by changing the benchmark against which buyers evaluate flood losses. This affects perceived utility, willingness to bid and property selection even when households face the same objective flood probability. The basic event-based loss formulation produced larger transaction-price discounts and utility gaps between flood-prone and non-flood-prone properties than objective risk perception, particularly at 2% and 3% flood probability. Using expected future market value as the reference point generated broadly similar outcomes to the event-based loss formulation and did not consistently increase or decrease the flood-related penalty. Anticipated financial protection reduced the loss perceived by households, while recent and distant flood experiences represented changes in perceived risk associated with flood risk myopia and amnesia.

These individual evaluations translated into differences in transaction prices, utility, transaction frequency and residential sorting. Only anticipated financial protection of 80% under prospect theory reduced flood-zone differences below those produced under objective risk perception, while distant flood experience under subjective weighting generated outcomes closest to the objective risk scenario. Reference-point effects were most visible at lower flood probabilities and generally narrowed at 5% risk, when objective exposure became increasingly influential across all formulations.

Household heterogeneity in probability weighting and loss aversion also contributed to spatial sorting, as stronger behavioural responses to flood risk were generally associated with

residence outside the flood zone, although the effect of probability weighting was more pronounced than loss aversion strength. Higher demand further strengthened sorting, with lower-income households becoming more concentrated in flood-prone areas while wealthier households were able to afford their way to safety. Reference-point selection and behavioural heterogeneity therefore meaningfully affect both individual housing choices and the distribution of flood exposure across the wider housing market.

These conclusions should be interpreted as evidence of behavioural mechanisms and relative differences between scenarios rather than as precise forecasts for the Limburg housing market. Each reference point was evaluated separately to isolate its effect, whereas households may combine several benchmarks when making actual housing decisions. The behavioural parameters were also derived from existing literature and held stable throughout each simulation. Consequently, the results demonstrate how alternative reference points can influence market outcomes, but do not establish which reference points households use in practice or predict the exact magnitude of their effects.

Policy implications and recommendations

The results demonstrate that flood risk policy influences housing markets not only by changing objective exposure, but also by shaping how households perceive and evaluate potential losses. Policies concerning risk communication, financial protection and housing affordability may therefore affect transaction prices, market activity and the socioeconomic distribution of flood exposure. The stakeholder analysis in Table 2 identifies the national government, municipalities and the Province of Limburg, Waterschap Limburg, and financial institutions as the actors with the greatest ability to influence these conditions. Households and real estate agents have less formal power, but their collective choices and practices determine how policy and risk information become reflected in the housing market. The recommendations are therefore directed towards the stakeholders capable of changing institutional conditions while also recognising the roles of market participants.

Anticipated financial protection reduced differences between properties within and outside the flood zone, although only the highest tested protection level of 80% produced smaller differences than objective risk perception. The national government should therefore provide clear and credible information about the eligibility conditions, scope and limitations of public compensation. This could reduce uncertainty and prevent households from either overestimating their personal financial exposure or assuming that all losses will be compensated. Insurers should similarly communicate the availability and limitations of relevant coverage, while mortgage lenders should consider how residual flood risk and household adaptation affect long term financial vulnerability. Financial protection should therefore also be clear about uninsured risks and incentivise property level adaptation. Otherwise, extensive protection may encourage households to accept properties with substantial objective risk without this risk being reflected in property valuation.

The concentration of lower income households in flood prone areas indicates that flood risk may also become an issue of distributive justice. Under high demand pressure, wealthier households have greater purchasing power to obtain safer properties, while households with

fewer alternatives remain concentrated in relatively affordable but more exposed locations. Waterschap Limburg should therefore continue to prioritise collective flood protection in cooperation with national, provincial and municipal authorities. Measures such as dike reinforcement, water storage and improved drainage reduce objective risk independently of household purchasing power or behavioural risk perception. Collective protection can consequently provide a redistributive benefit by reducing expected damage where private adaptation capacity is lowest.

Municipalities and the Province of Limburg should complement collective protection with spatial planning and housing measures that address the distributional consequences identified by the model. These may include targeted adaptation subsidies for financially vulnerable households, protection of affordable housing in areas receiving public investment and relocation assistance where risk cannot be sufficiently reduced. Such measures are important because improved protection may increase property values and rents, potentially displacing existing residents. Public flood defence and housing affordability should therefore be considered jointly rather than as separate policy domains. Since public defence investments and affordability measures were not directly simulated, these recommendations follow from the observed sorting patterns rather than tested intervention effects.

Differences in flood experience, probability weighting and loss aversion also demonstrate that uniform risk communication is unlikely to affect all households equally. Waterschap Limburg and local authorities should repeat risk information over time to counter declining awareness during long periods without flooding. Communication should explain both flood probabilities and understandable financial consequences, including residual risk after protective measures. The national government could support this by establishing consistent requirements for property level flood risk disclosure. Real estate agents could then communicate this information during the purchasing process, while mortgage lenders and insurers could incorporate it into financing and coverage discussions. Standardised disclosure should combine expected damage, residual risk, available compensation, insurance options and practical adaptation measures.

Households remain responsible for property choices, but they should not be expected to independently interpret complex probability and damage information. Accessible and comparable information would allow them to evaluate properties more deliberately and reduce reliance on recent personal experience or assumptions about public protection. Because individual real estate agents and households have limited influence over the wider system, consistent standards and institutional support are necessary for these individual actions to collectively improve market transparency.

Together, these recommendations assign responsibility according to the influence and role of each stakeholder. National and regional authorities shape compensation, planning and housing policy, Waterschap Limburg manages collective protection and communicates residual risk, financial institutions influence financial exposure, and real estate agents transmit property information to households. These recommendations should be interpreted as policy implications derived from the behavioural and spatial mechanisms observed in the model rather

than as tested intervention effects. Public flood defences, affordability measures, mortgage decisions, insurance arrangements and the actions of institutional stakeholders were not modelled directly. Their effectiveness and potential unintended consequences should therefore be evaluated through empirical research, stakeholder consultation and dedicated policy experiments before implementation.

Scientific & societal contribution

Beyond the policy implications, this study also offers broader insights for research and practice. Reflecting on these contributions helps clarify how the work builds on existing knowledge and why its findings matter in the real world outside the model. The following sections discuss how the research extends the literature on flood risk and housing markets, develops behavioural modelling approaches and supports real world stakeholders facing unequal flood exposure and difficult housing decisions.

Scientific contribution

The scientific contribution of this study lies in integrating several previously separated strands of literature into a unified behavioural housing market framework. Hedonic studies demonstrate that flood exposure is capitalised unevenly into property prices, but provide limited insight into the individual decision processes producing these discounts (Bin & Landry, 2013; Mutlu et al., 2023). Research on subjective risk perception shows that experience, information and expectations of financial protection alter how households interpret identical objective risks (Gallagher, 2014; Mol et al., 2020). Housing research further demonstrates that valuations depend on reference points, including purchase prices, ownership and market expectations (Genesove & Mayer, 2001; Tomal, 2024b). Agent based models can connect such individual evaluations to aggregate market outcomes, but existing flood risk applications generally represent prospect theory using a predetermined reference point or examine changing risk perception as a separate mechanism.

This study addresses this gap by operationalising multiple theoretically and empirically informed reference points within the same prospect theory framework. Single and event based flood losses, expected future market value, anticipated financial protection and changing risk perception following flood experience are translated into comparable household utility formulations. Embedding these formulations within the same RHEA NL housing market structure allows their effects to be isolated while keeping market processes and external conditions consistent. The revised utility to bid price mapping further connects reference dependent evaluations to monetary bids, transactions and residential sorting.

The results provide new academic insight by demonstrating that reference point selection is not a neutral modelling assumption. Different formulations of the same objective flood risk generate differences in utility, bidding, transaction prices, market activity and the distribution of households between flood zones. The study therefore extends existing prospect theory applications from testing behaviour under one assumed benchmark towards analysing the consequences of competing benchmarks. It provides a reusable framework for comparing behavioural assumptions and generates testable propositions for future surveys, choice

experiments and housing market models seeking to identify which reference points households actually apply.

Societal contribution and implications

The societal contribution of this study lies in demonstrating that managing physical flood probability alone is insufficient to understand housing market vulnerability. Households are not only decision makers within this system, but also the people who bear the financial, residential and safety consequences of their choices. Different interpretations of the same objective risk may lead households to overestimate or underestimate potential losses, influence how much they bid and affect whether they settle within or outside the flood zone. These decisions can shape their exposure to property damage, changes in property value and future relocation costs. By connecting individual evaluations to market outcomes, the research shows how behavioural differences can accumulate into wider patterns of vulnerability.

The findings are therefore relevant to the stakeholders identified in Table 2. Clear information from the national government about public compensation can help households understand which losses remain their responsibility. Risk communication from Waterschap Limburg and local authorities can maintain awareness of residual risk, particularly during long periods without flooding. Municipalities and the Province of Limburg can consider the relationship between flood exposure, housing affordability and access to adaptation support. Mortgage lenders, insurers and real estate agents can contribute by presenting property level risk, financial consequences and available protection consistently during financing and purchasing decisions. These actions can help households compare properties more deliberately rather than relying mostly on recent experiences or assumptions about public protection.

The study also highlights that households are not affected equally. Lower income households may have fewer opportunities to avoid exposed areas or finance property level adaptation, while wealthier households possess greater capacity to obtain safer housing. Behavioural and financial differences may therefore reinforce the concentration of vulnerable households in flood prone locations. The societal value of this research lies in connecting flood protection, market information, housing affordability and household heterogeneity within one socio technical perspective. Although the proposed interventions were not directly tested, the model provides a structured basis for stakeholder dialogue and for developing policies that support informed housing choices while reducing unequal flood exposure.

Concluding statement

This research demonstrates that housing decisions under flood risk cannot be understood through objective probabilities and expected losses alone. The reference points used by households, together with differences in probability weighting, loss aversion and flood experience, influence how risk is translated into utility, bids and property choices. Through repeated market interactions, these individual evaluations affect transaction prices, market activity and the spatial distribution of households. Reference-point selection is therefore an important modelling choice with consequences for both market performance and inequality. As objective flood probability increased, differences in price discounts and several sorting patterns

narrowed, while utility and activity remained differentiated. Housing demand strengthened competition for safer properties and generally increased the concentration of lower-income households in flood-prone areas. Similar market prices can therefore conceal different household evaluations and unequal exposure.

The findings support considering physical flood protection alongside financial support, transparent compensation arrangements and clear, accessible and repeated risk communication. These measures should account for behavioural differences and unequal purchasing power while maintaining awareness of residual risk. Their effectiveness requires further investigation, since the model did not directly test these policy interventions. Incorporating reference-dependent decision-making into housing-market analysis provides a more complete understanding of how flood exposure becomes reflected in both market outcomes and socioeconomic vulnerability in the Limburg river area.

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Appendix

A. Verification Charts

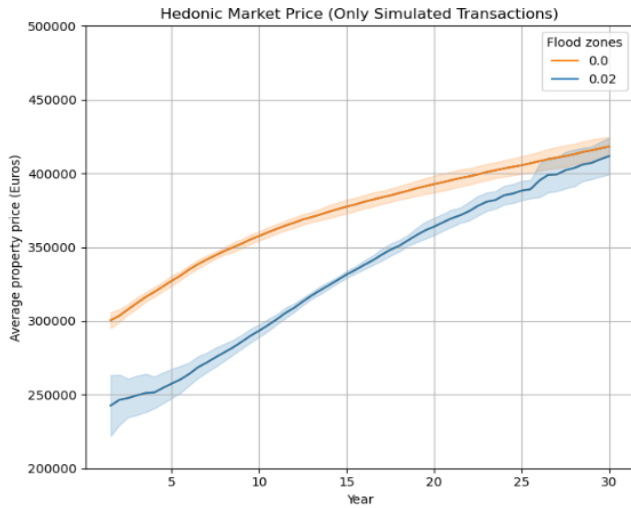


Figure A1. Average realtor market value of sales

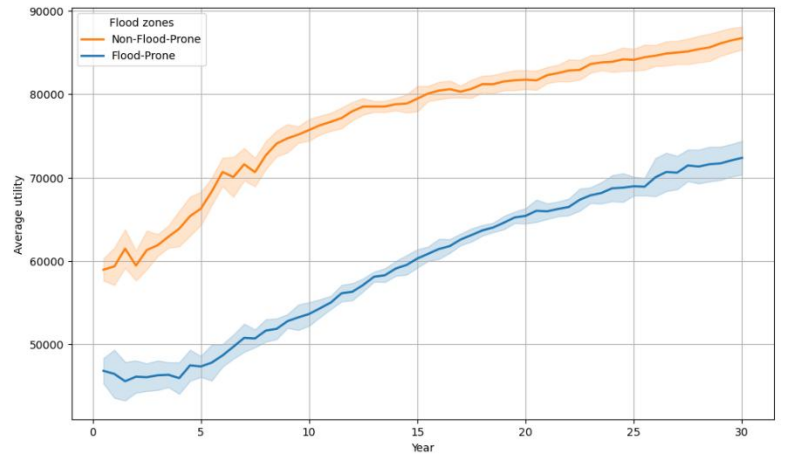


Figure A2. Average utility of placed bids

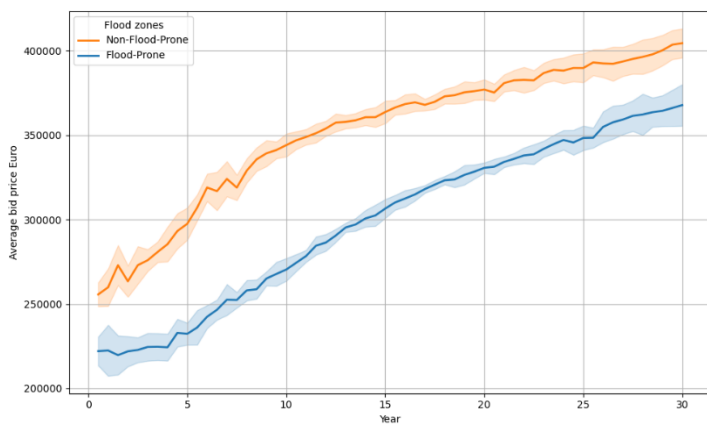


Figure A3. Average bid price on properties

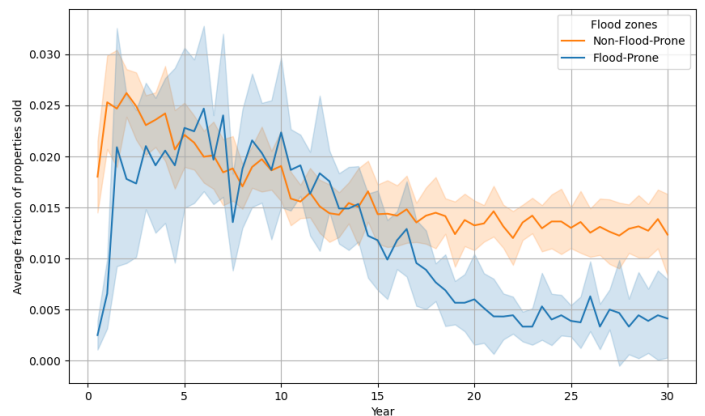


Figure A4. Average fraction of properties sold

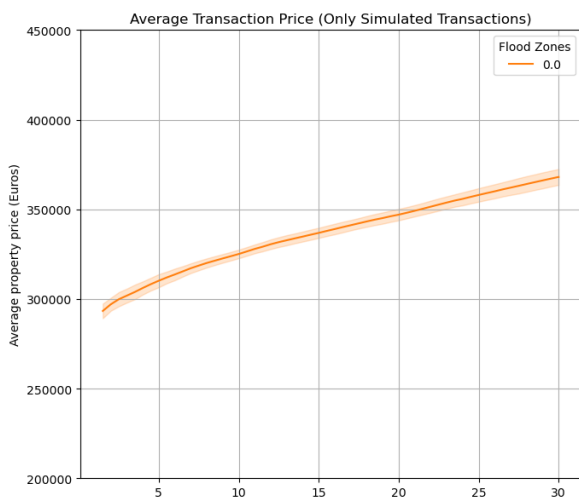


Figure A5. Transaction prices without flood risk

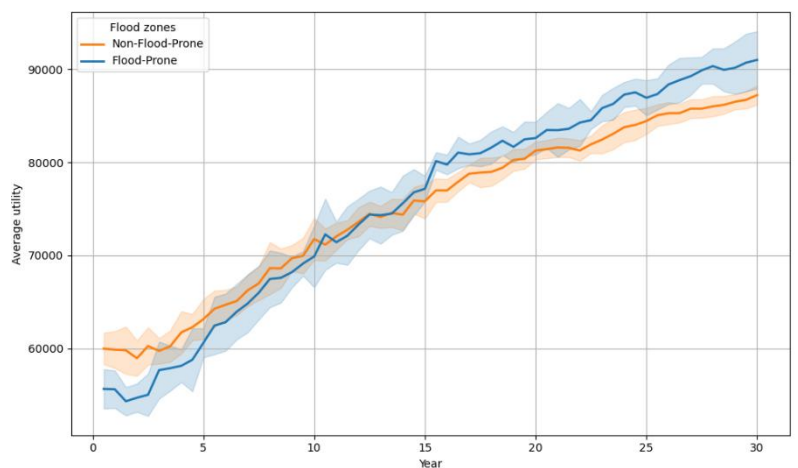


Figure A6. Average utility without flood risk

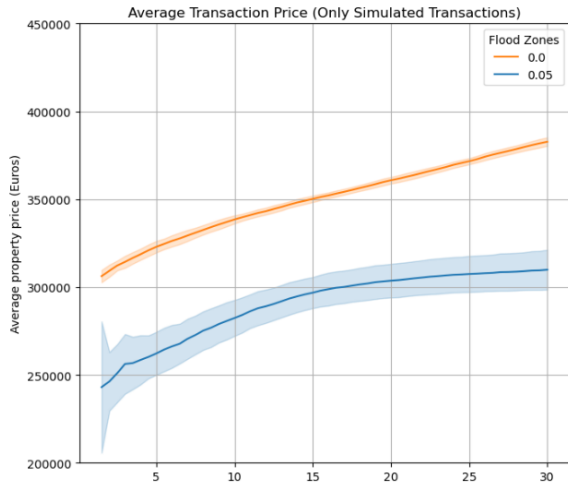


Figure A7. Transaction prices at high flood risk

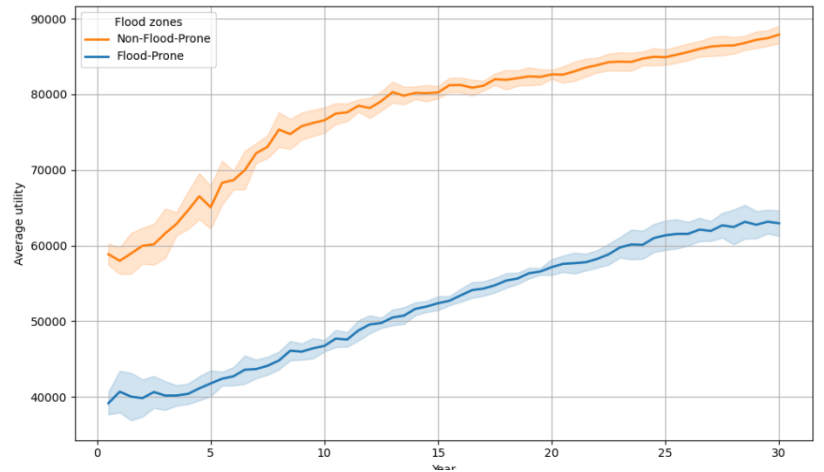


Figure A8. Average utility at high flood risk

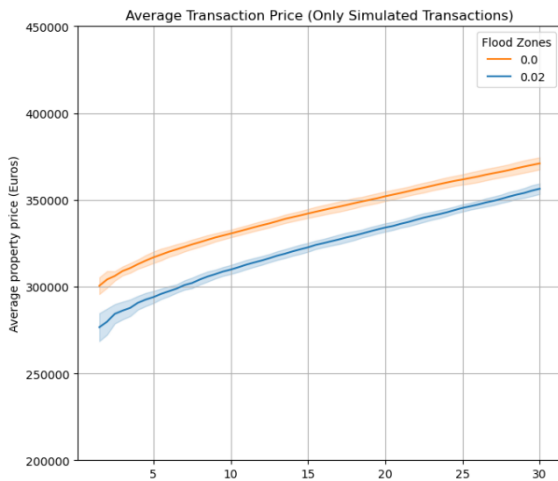


Figure A9. Transaction prices with loss aversion at 0

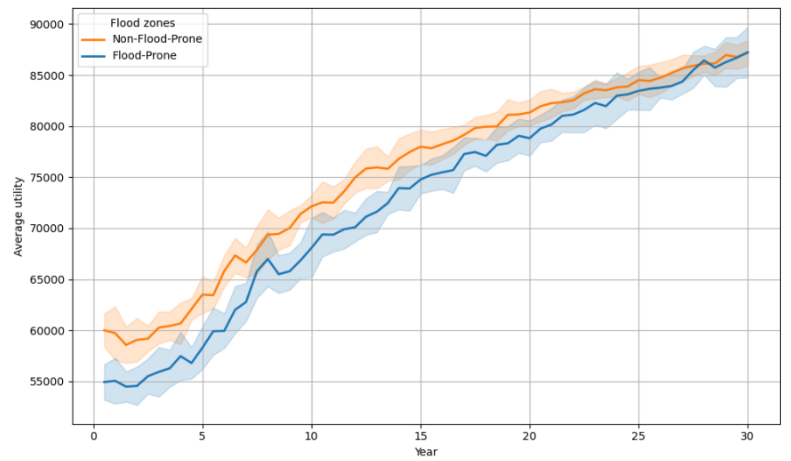


Figure A10. Average utility with loss aversion at 0

B. Validation Charts

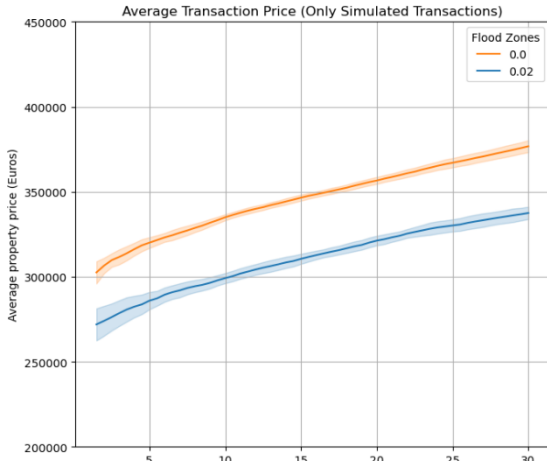


Figure B1. Average baseline transaction prices

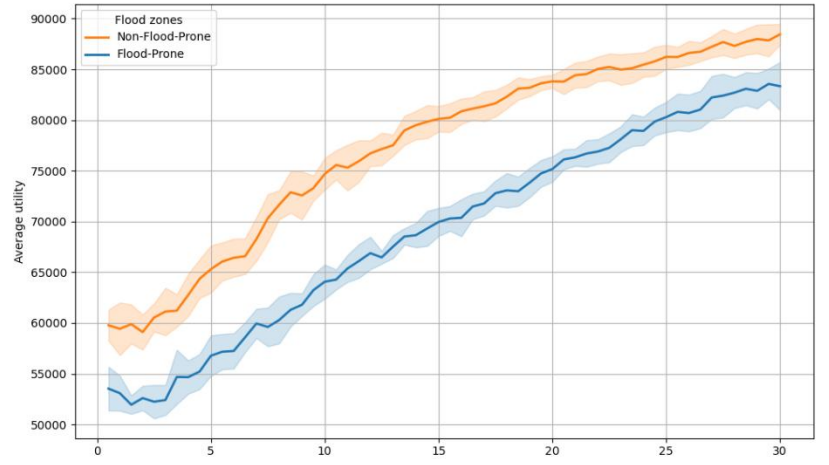


Figure B2. Average utility of bids placed

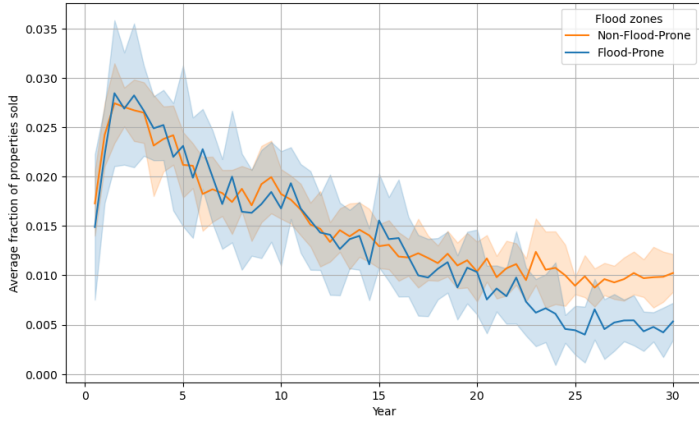


Figure B3. Average fraction of properties sold, baseline

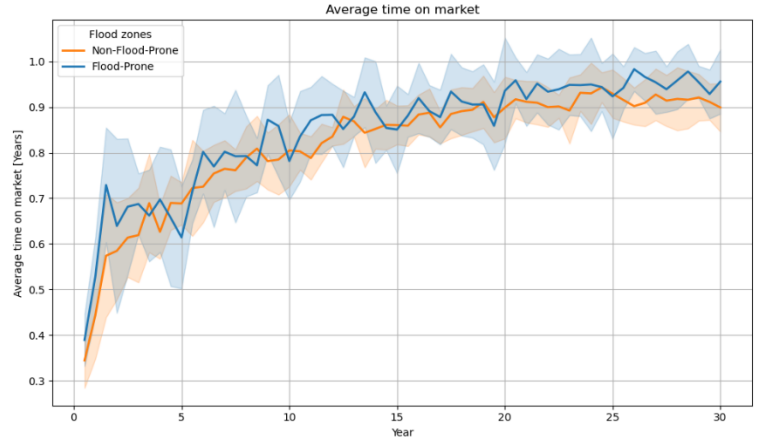


Figure B4. Time for sale of properties

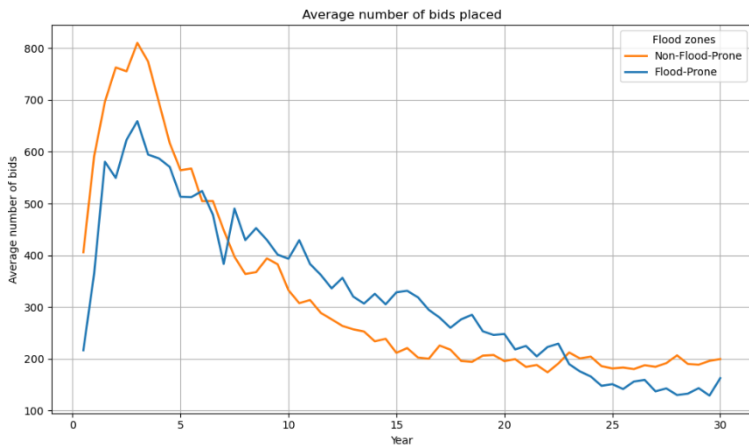


Figure B5. Average number of bids placed, baseline

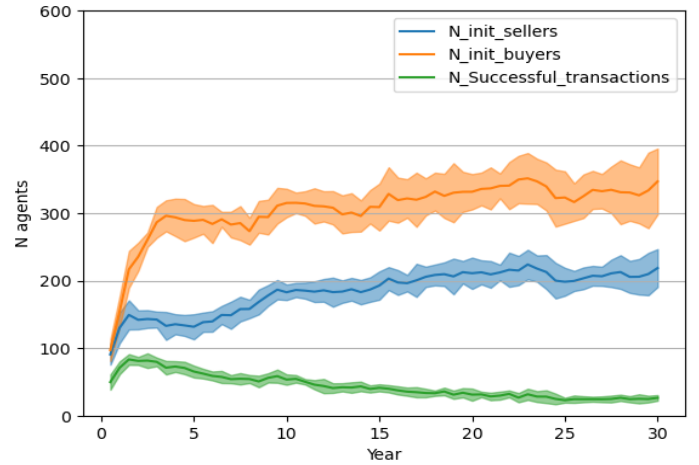


Figure B6. Number of buyers, sellers and transactions

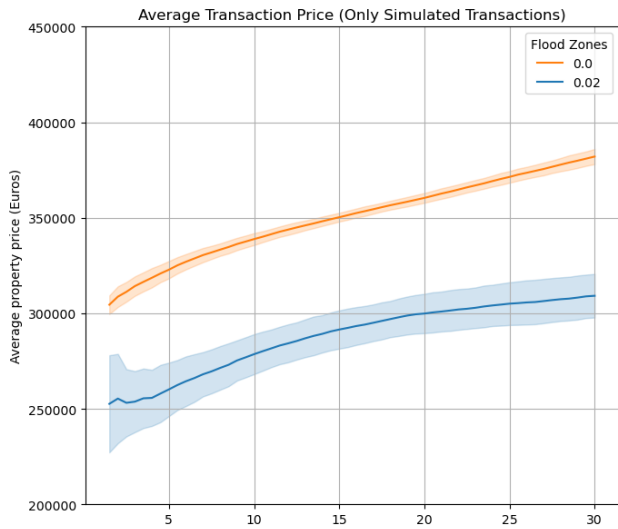


Figure B7. PTNullS average transaction prices

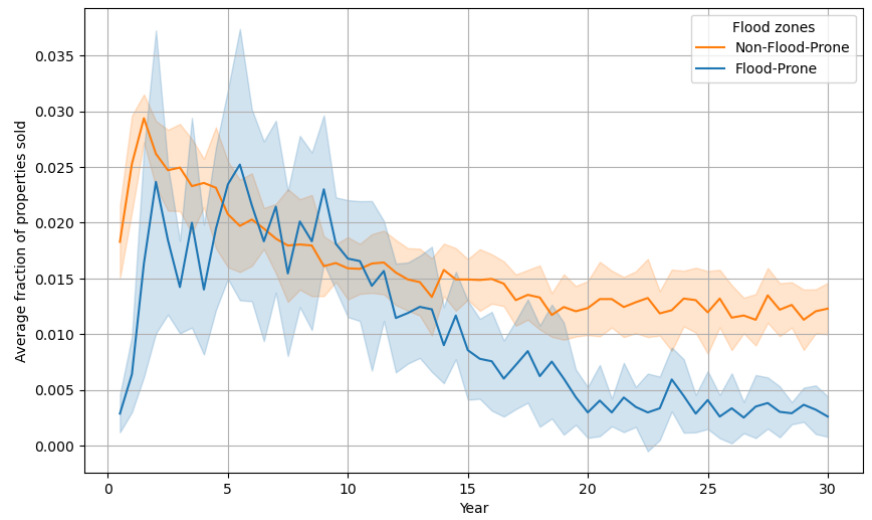


Figure B8. PTNullS average fraction of properties sold

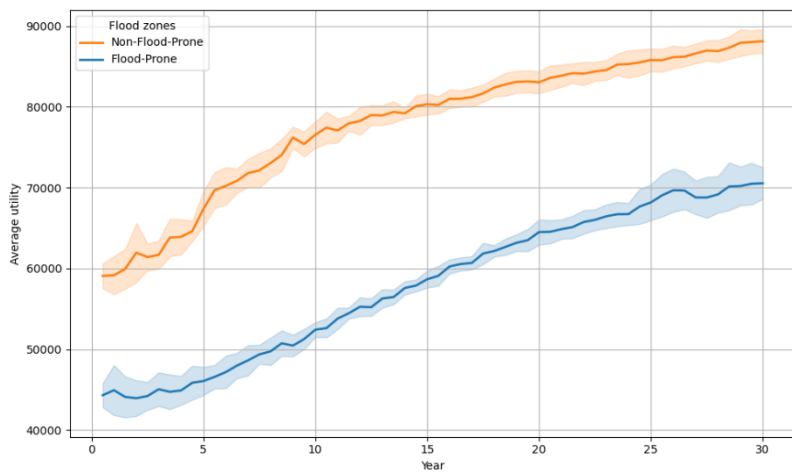


Figure B9. PTNullS average utility of bids

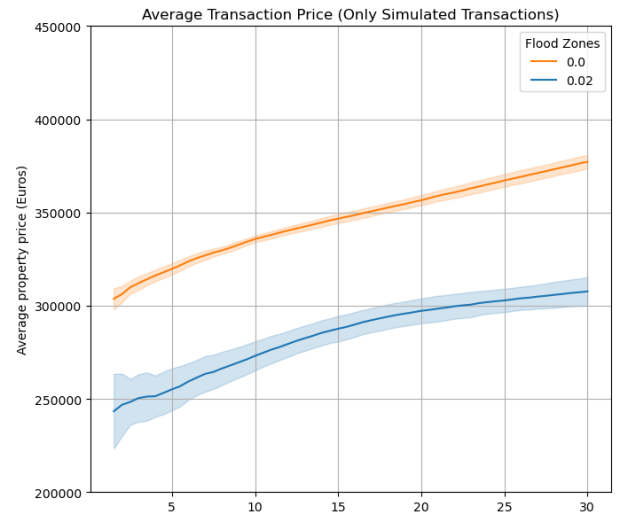


Figure B10. PTNullC average transaction prices

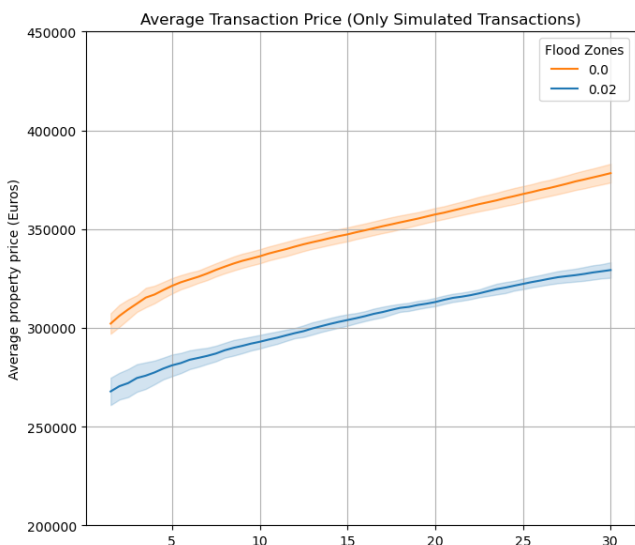


Figure B11. PTFP moderate, average transaction price

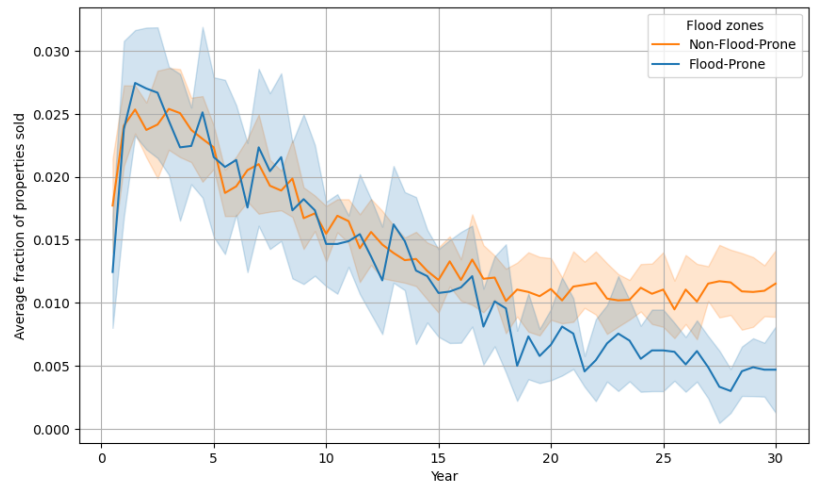


Figure B12. PTFP moderate, average fraction of properties sold

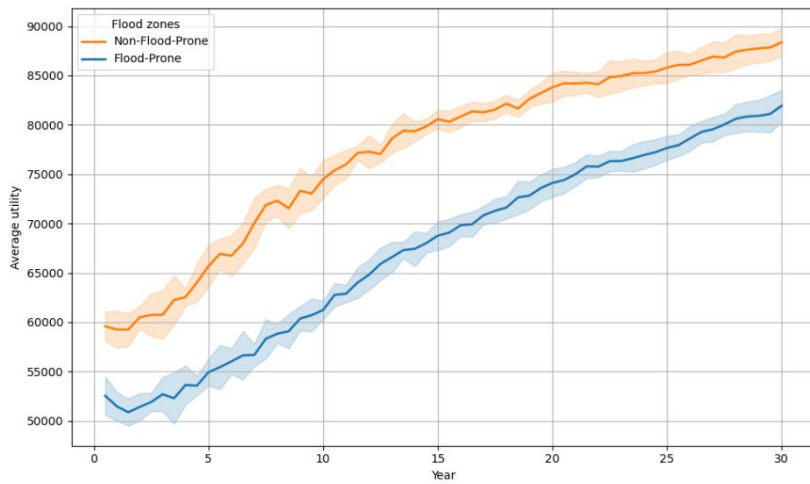


Figure B13. PTFP moderate, average utility of bids

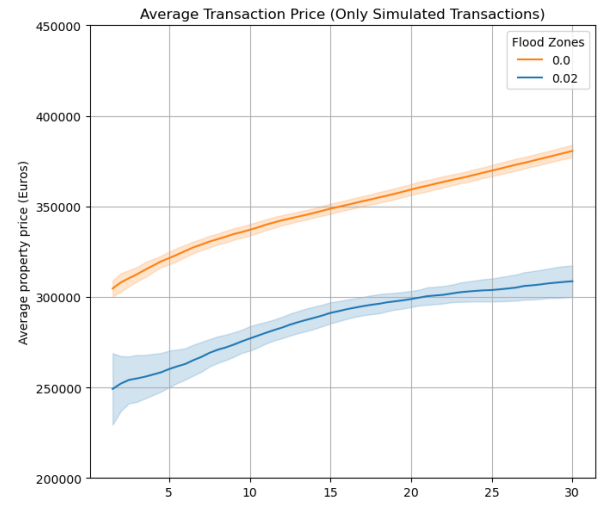


Figure B14. PTEMV average transaction prices

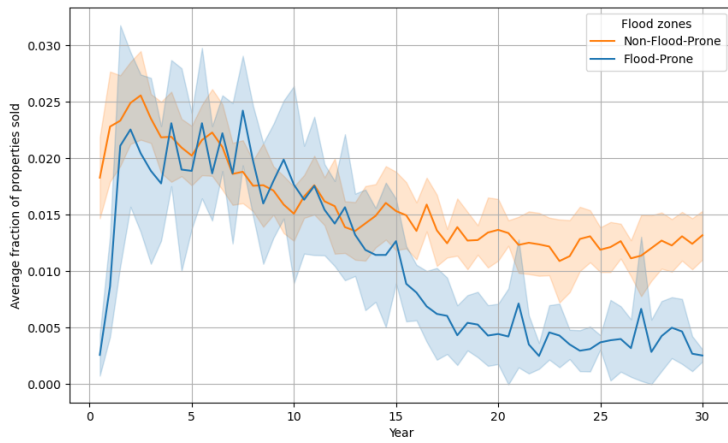


Figure B15. PTEMV average fraction of properties sold

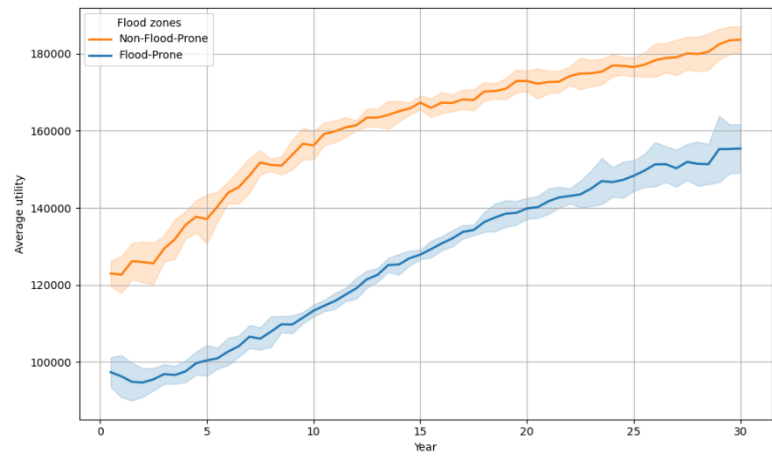


Figure B16. PTEMV average utility of bids

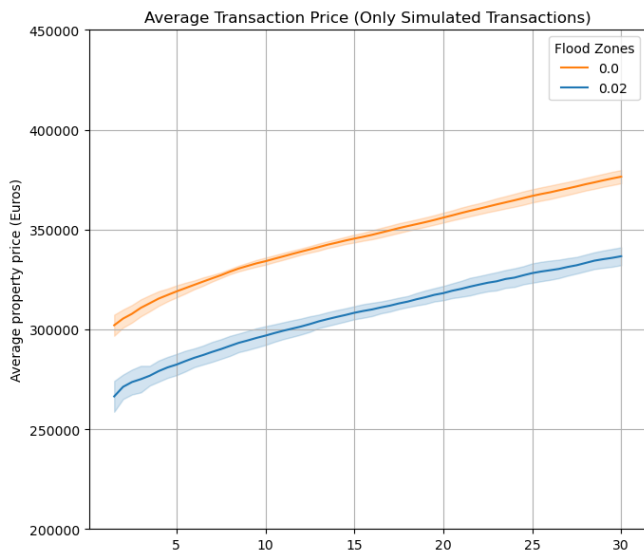


Figure B17. PTDR distant average transaction prices

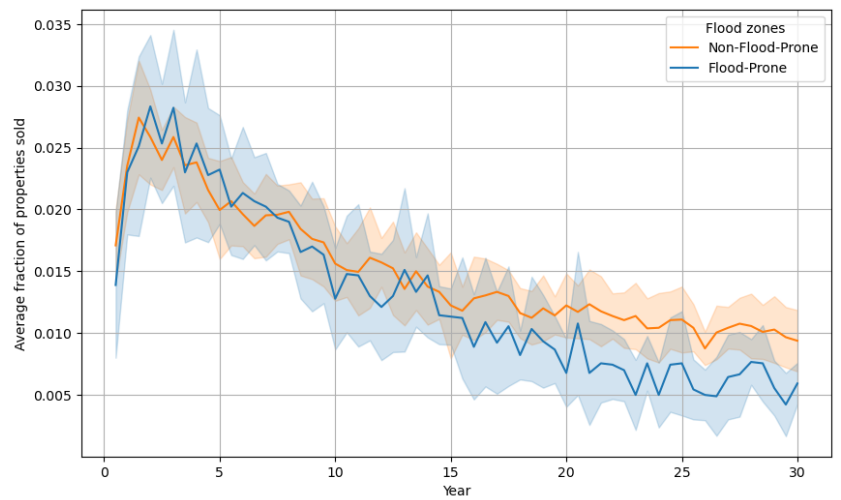


Figure B18. PTDR distant, average fraction of properties sold

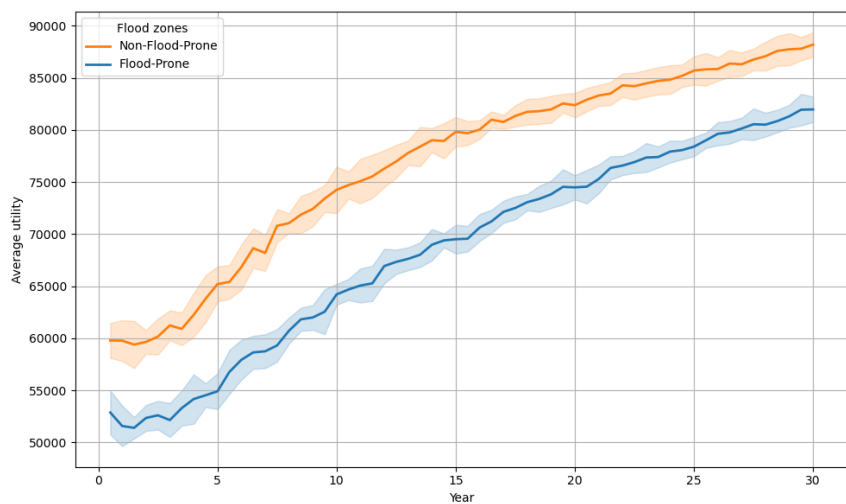


Figure B19. PTDR distant, average utility of bids

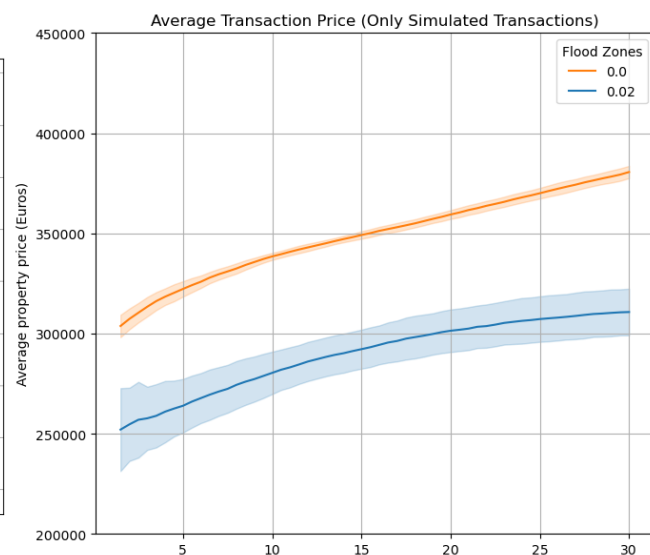


Figure B20. PTDR recent, average transaction prices

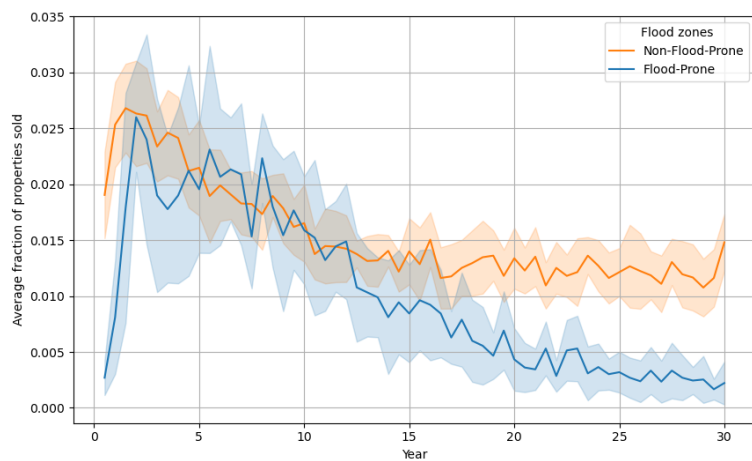


Figure B21. PTDR recent, fraction of properties sold

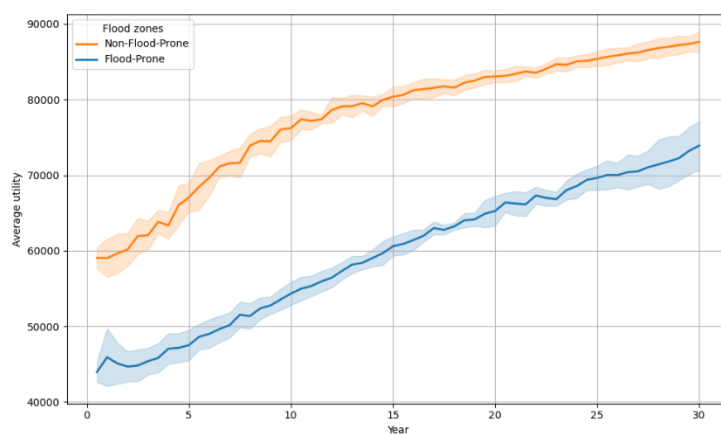


Figure B22. PTDR recent, average utility of bids

C. Results

Figures C1 to C4 show how the average number of bids develops in both flood zones under high demand. They support the discussion of declining market activity and the difference between bidding activity and completed transactions.

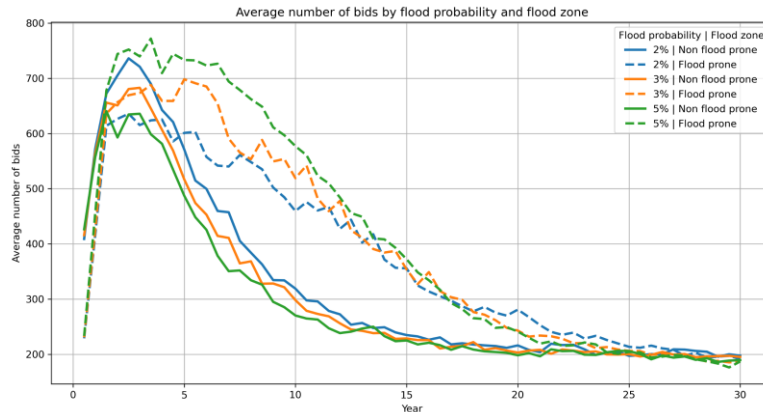


Figure C1. Base, high demand, number of bids averaged over 50 Monte Carlo simulations.

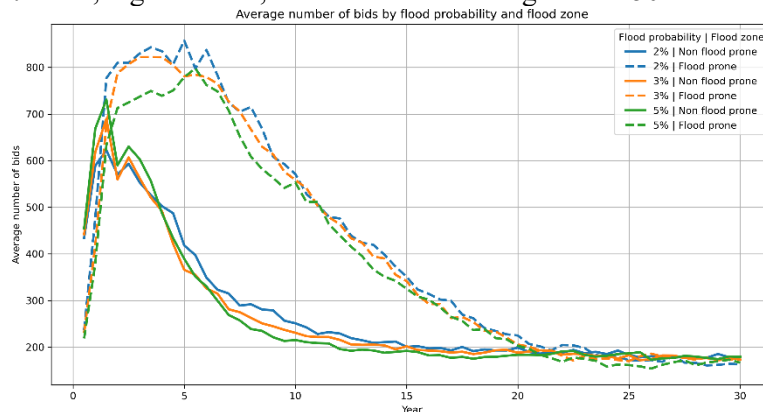


Figure C2. PTNullC, high demand, number of bids averaged over 50 Monte Carlo simulations.

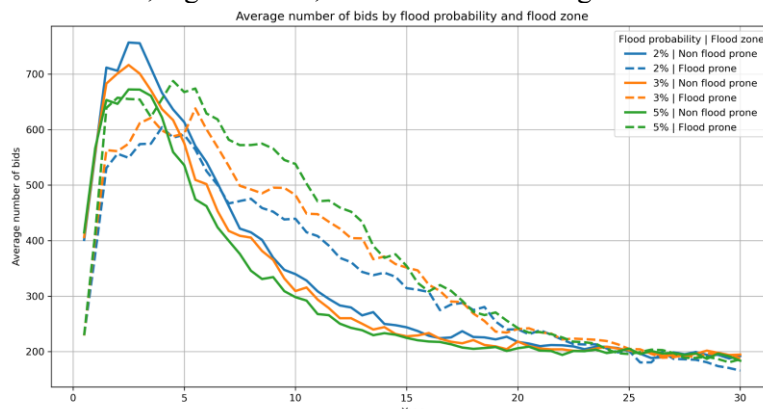


Figure C3. PTFP high, high demand, number of bids averaged over 50 Monte Carlo simulations.

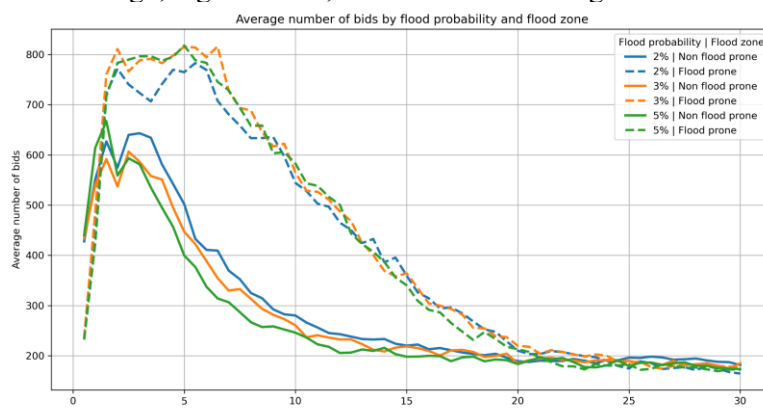


Figure C4. PTDR moderate, high demand, number of bids averaged over 50 Monte Carlo simulations.

Table C1. Final year absolute income

Demand: Medium	2%			3%			5%		
<i>Scenario</i>	Non-flood (€)	Flood prone (€)	Gap (%)	Non-flood (€)	Flood prone (€)	Gap (%)	Non-flood (€)	Flood prone (€)	Gap (%)
Base	51,683	42,753	17.3	51,920	42,383	18.4	52,165	41,913	19.7
PTNullS	53,124	41,305	22.2	53,257	41,105	22.8	53,391	40,647	23.9
PTNullC	52,820	41,444	21.5	53,009	41,161	22.4	53,450	40,939	23.4
PTEMV	52,882	41,360	21.8	53,109	41,318	22.2	53,293	40,839	23.4
PTFP low	52,453	42,154	19.6	52,758	41,550	21.2	53,012	41,469	21.8
PTFP med	52,030	42,416	18.5	52,236	42,142	19.3	52,737	41,644	21.0
PTFP high	51,514	43,371	15.8	51,828	43,037	17.0	51,939	42,389	18.4
PTDR recent	52,712	41,418	21.4	53,001	41,157	22.3	53,306	40,908	23.3
PTDR moderate	52,299	42,066	19.6	52,543	41,795	20.5	52,852	41,405	21.7
PTDR distant	51,696	42,762	17.3	51,905	42,385	18.3	52,350	41,890	20.0
Demand: High	2%			3%			5%		
Base	61,377	50,035	18.5	61,531	48,532	21.1	62,506	47,785	23.6
PTNullS	63,285	46,481	26.6	63,818	47,025	26.3	64,111	46,431	27.6
PTNullC	62,991	46,618	26.0	63,495	46,738	26.4	63,880	46,834	26.7
PTEMV	63,331	47,151	25.5	63,638	47,055	26.1	63,989	46,359	27.6
PTFP low	62,043	47,803	23.0	62,571	47,076	24.8	63,330	46,649	26.3
PTFP med	61,630	48,925	20.6	62,204	47,922	23.0	62,601	47,198	24.6
PTFP high	60,645	50,823	16.2	60,987	49,978	18.1	61,537	48,922	20.5
PTDR recent	62,943	46,844	25.6	63,484	47,072	25.9	63,666	46,845	26.4
PTDR moderate	62,035	47,684	23.1	62,441	47,357	24.2	63,272	47,143	25.5
PTDR distant	61,065	49,787	18.5	61,604	48,891	20.6	62,064	47,704	23.1

AI Assistance Statement

During the preparation of this thesis, OpenAI's ChatGPT was used to support language editing, document structure, code development and the presentation of results. Consensus AI was used to locate relevant literature supporting specific statements and providing additional context. All generated content, code and suggested sources were reviewed and verified by the author. The author remains fully responsible for the research design, analysis, interpretation, conclusions and final content of this thesis.